AI Application in Transport and Logistics

Opportunities and Challenges (An Exploratory Study)

Author(s)
El Makhloufi, Abdel

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AI Application in Transport and Logistics Opportunities and Challenges (An Exploratory Study)

Abdel El Makhloufi

Amsterdam University of Applied Sciences, Faculty of Technology
CoE City Net Zero, Amsterdam

Amsterdam University of Applied Sciences

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Authors
Abdel El Makhlouf (AUAS, Research group ‘Mainport Logistics’)

Design
A. El Makhloufi

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Contact
Dr. Abdel El Makhloufi. Amsterdam University of Applied Sciences (AUAS), Faculty of Technology. REsearch group Mainport Logistics/CoE CIty Net Zero. JMH-Rijnspoortplein 21091 GC Amsterdam, The Netherlands. Internet: http://www.international.hva.nl

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AI APPLICATION IN TRANSPORT AND LOGISTICS

OPPORTUNITIES AND CHALLENGES (AN EXPLORATORY STUDY)

Content

List of Figures

List of Tables

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Acronyms and abbreviations

AI: Artificial Intelligence.

DSS: Dutch Digitalisation Strategy.

NL-AIC: Netherlands AI Coalition (Nederland AI-Coalitie).

IoT: Internet of Things.

5G: 5G networks.

MTL: Mobility, Transport and Logistics.

NOW: Dutch Organization for Scientific Research.

CWI/VU: Centrum voor Wiskunde & Informatica/Vrije Universiteit.

HAN: Hogeschool van Arnhem-Nijmegen.

ML: Machine Learning.

MRA: Metropolitan Region Amsterdam

DDS: Dutch Digitalisation Strategy

NL AIC MTL: NL AI Coalition 'Mobility, Transport and Logistics'

CWI: Center for Mathematics and Informatics

MRA: Metropolitan Region Amsterdam

ML: Machine Learning

DL: Deep Learning

SVM: Support Vector Machine

CNN: Convolutional Neural Networks

RNN: Recurrent Neural Networks

LSTM: Long Short-Term Memory

GANs: Generative Adversarial Networks

NLP: Natural Language Processing

IDS: International Data Spaces

ELSA: Ethical, Legal and Societal Aspects

ICAI: Innovation Centres for AI

NOW: Netherlands Organization for Scientific Research

eCMR: electronic Convention for the Carriage of Goods (“Contrat de Transport International de Marchandises par Route”)

CRM: Costumer Resources Management

CAV: Car Autonomous Vehicle

UAV: Unmanned Aerial Vehicle

PAV: Personal Aerial Vehicle

ITS: Intelligent Transportation System

TMS: Traffic Management System

ITMS: Integrated Traffic Management System

RPA: Robotic Process Automation

ERP: Enterprise resource planning

ETA: Estimated Time of Arrival

ETD: Estimated Time of Departure

VTS: Vessel Traffic Services

ATC: Air Traffic Control

A-CDM: Airport Cooperative Decision Making

ATFCM: Air Traffic Flow Management

XAI: eXplainable Artificial Intelligence

REDA: Readback Error Detection Assistant

Introduction

1. Introduction

The Dutch economy is largely driven by the services and transport and logistics sectors. The Metropolitan regions of Amsterdam (where Schiphol and Port of Amsterdam are located), Rotterdam (Port of Rotterdam), and Eindhoven (High-tech cluster) provide a large part of the earning capacity from these two sectors to the Dutch economy. However, the two mainports regions of Amsterdam and Rotterdam face complex (economic, technological, social) challenges in the coming decades, particularly in the areas of sustainability of mobility, transport and logistics, accessibility, emissions, safety, and increasing pressure on available space for citizens and businesses.

Developing and effectively deploying Artificial Intelligence (AI) from an integrated ecosystem approach, both at the level of people and objects and at the level of systems and processes, can help to tackle these challenges and contribute to accelerating transitions to better accessibility, sustainability and reduction of environmental damage/emission-free mobility, transport and logistics in the city and the metropolitan region.

In The Netherlands, the government has set out a first integrated approach to digitalization for the purpose of managing the digital transition in production and services, communication, and societal processes (see Dutch Digitalization Strategy (DDS), 2018). The aim is to make responsible use of the opportunities presented by digitalization and automatization using AI technology and systems. The strategy featured a two-pronged approach: scaling up the capabilities of digital applications within domains and creating the foundations and preconditions for this to happen, such as security and privacy. Artificial Intelligence (AI) has been identified as one of the innovation spearheads in Dutch knowledge development for the coming years. However, compared to global leaders such as China and the USA, the application of AI (smart cities, security, etc.), The Netherlands (and Europe) is lagging.

To close the gap with these forerunners countries in the world, The Dutch government founded The Netherlands AI Coalition (NL AIC) at the end of 2019 to develop a strong infrastructure and high-quality business eco-system of Dutch AI activities. It is a public-private partnership in which governmental authorities, the commercial sector, educational and research institutions, and social organizations work together to accelerate AI developments in the Netherlands and link AI initiatives in the country to one another.

One initiative that is intended to lead to the Netherlands remain in the international vanguard of AI is the development of the AiNed investment program, of which Phase 1 was implemented in the spring of 2021 thanks to the National Growth Fund (NGF). This is an integral, long-term public-private investment program for research and innovation.

The development of AI systems and applications in mobility, transport, and logistics sectors is sought by the Dutch government as one of the main elements of The Netherlands IA eco-system. This is because Mobility and transport make an important contribution to the Dutch economy. It is important to remain competitive in relation to other countries, to safeguard the function of the Netherlands as a logistics hub, and to raise the level of mobility services in order to also secure the leading position in "Smart Mobility".

However, in the Netherlands, mobility and transport are characterized by heavy traffic, densely populated cities, and many national and international transport and logistics movements. The increasing number of traffic movements of people and goods is important from an economic point of view but poses a major challenge when it comes to road safety, CO_2 emissions, air quality, and traffic flow.

Urgency/need change towards future-proof mobility and transport in terms of sustainable, accessible, affordable, livable, inclusive, and safe with positive economic and employment impacts. These are all important social factors that drive innovation.

This can be achieved through the introduction and use of new technologies and technological developments, in addition to extensive digitization and automation (IoT, 5G, AI, etc.).

Innovation is a means. The goal is a transport and mobility system that transports people and goods safely, sustainably, efficiently, and reliably and that ensures a healthy revenue model and economic climate. In this system, people, vehicles, and their environment are constantly interacting, and smart solutions are needed to facilitate this interaction.

AI enables (accelerates) disruptive technological applications in transport and logistics, such as self-driving cars, new energy carriers, smart grids, predictive maintenance, cooperative mobility, self-organizing logistics systems/platforms, etc.

1.1. Background

Since 2020, AUAS (Mainport Logistics) has been a member of the NL AI Coalition Mobility, Transport and Logistics (NL AIC MTL). The NL AI-MTL working group focuses on the most important opportunities and challenges in the development and application of AI for sustainable mobility, AI for accessibility and flow, AI for safe, shared, and flexible mobility (e.g. smart self-driving vehicles, public transport), and AI for efficient logistics (including smart planning systems, predictive maintenance, self-organizing logistics). Together with the Center for Mathematics and Informatics (CWI) and VU, we represent the hub region of North Holland. The goal of this coalition is coordination and cooperation. The coalition also wants to check whether there is a certain focus or specialization for the regions by collaborating with the various parties from the region on concrete actions in innovation projects for long-term AI solutions for transport, mobility, and logistics.

1.2. Purpose/Goal and scope

The aim of this research/project is to investigate and analyze the opportunities and challenges of implementing AI technologies in general and in the transport and logistics sectors. Also, the potential impacts of AI at sectoral, regional, and societal scales that can be identified and channeled, in the field of transport and logistics sectors, are investigated. Special attention will be given to the importance and significance of AI adoption in the development of sustainable transport and logistics activities using intelligent and autonomous transport and cleaner transport modalities. The emphasis here is therefore on the pursuit of 'zero emissions' in transport and logistics at the urban/city and regional levels. Another goal of this study is to examine a new path for follow-up research topics related to the economic and societal impacts of AI technology and the adoption of AI systems at organizational and sectoral levels.

This study is based on exploratory analysis and focuses mainly on the examination of existing literature and (empirical) scientific research publications, previous and ongoing AI initiatives and projects (use cases), policy documents, etc., especially in the fields of transport and logistics in the Netherlands. It presents and discusses many aspects of existing challenges and opportunities that face organizations, activities, and individuals when adopting AI technology and systems.

1.3. Research questions

The main research question of this study is:

Which trends and developments are taking place at national and international levels with regard to the development and implementation of AI technology and systems, especially in the transportation and logistics sectors? What are the opportunities and challenges of adopting AI in the airport and port logistics sectors?

This study inventories possible sectoral, organizational, and societal effects of AI technology adoption, on the basis of the existing knowledge in the literature. In addition to an inventory of possible effects, we also draw up an overview of the most important uncertainties and possible follow-up research questions.

1.4. Approach and methodology

In this explorative study, we focus our attention on current existing literature and use cases on the main challenges and opportunities in the development and adoption of AI technology and systems, with a special focus on the transportation and logistics sectors. Hence, this study does not deal with the technological issues and design related to different types of AI technologies and systems nor the internal functionality and subsequent design and building blocks.

In short, this study provides a broad descriptive analysis of the importance and significance of AI technology and systems for organizations, the economy, and society. Special attention is also given to the opportunities and challenges of implementing AI technologies in economic sectors, individuals, and a group of individuals.

This research was carried out on the basis of an extensive literature study, supplemented by interviews with experts and companies operating in the transport and logistics sectors in the metropolitan region of Amsterdam.

First, we have reviewed what is already known about AI and the effects of AI at home and abroad in the literature. For the literature study, we use the (ex-ante effect) studies that have been carried out in the Netherlands. We have partly requested these within our network and partly we have found them via Google by searching for 'AI solutions', 'AI technologies', 'effects' of 'AI', etc. The reference list of the studies found also offered pointers for other relevant sources. We also searched for scientific literature (via Google Scholar, Science Direct, and Scopus) and for gray literature (via Google). To find relevant studies on AI and AI applications from other countries, we used the following search terms 'AI technologies', 'AI application' or 'effects of AI', etc., in combination with, among others, 'AI and ML' or 'AI and algorithms, etc. In addition, we have combined the last two search terms with the effects that we have identified in other studies.

We divide the various effects that we find in the literature into social effects that influence transport, logistics, mobility and accessibility, living environment, traffic performance, effects on the economy, and possible spatial implications. We summarize all these effects in an overview figure and various sub-figures.

Second, and in addition to the literature study, we have interviews with experts and companies active in the AI world, such as people from science, policy, and the professional field, in particular people and companies in transport and logistics in the mainport MRA region (see appendix of the list of interviews and participants).

The aim of the interviews was to verify the literature search and to test the overview figure with all information and possible results. We asked the experts to answer the following questions:

- What are the main trends and developments in the design, adoption, and implementation of AI technology and systems in transport and logistics?
- What are the challenges to adoption and opportunities offered by AI technology in transport and logistics sectors?
- Which activities and sub-activities, and organizational and operational processes will be most affected by the adoption of AI systems in transport and logistics?
- Which type of AI technology and applications will have the most impact on individuals, the society, and the economy, living environment and traffic and transport system?
- Which trends can we expect in the short term (1-5 years) and in the longer term (5-10 years) concerning the implementation of AI innovative solutions in these two sectors?

1.5. Reading guide

This report is organized as follows: Chapter 1 introduces the study, providing background information, goals, scope, research questions, and applied methodology in this research. Chapter 2 presents and discusses the definition and the main components of AI technology, as well as their significance for its deployment in businesses and society. Additionally, the chapter provides an overview of the actual development and evolution of AI technology and the international AI market in different fields, sectors, and regions of the world, based on the most recent available statistics and data. Various aspects related to data use and sharing for the deployment of AI are also discussed in this chapter.

Chapter 3 focuses on the development of the AI ecosystem initiated by the Dutch government in collaboration with the NL-AI coalition. The chapter presents and discusses the investments and efforts made by NL-AIC to create innovation centers and ELSA labs that foster the creation and development of an advanced digital AI ecosystem in The Netherlands. This chapter provides an extensive overview of the most known practical use cases and pilot projects that have been started and executed in various sectors and areas of application in The Netherlands. The chapter concludes with a similar focus on global practical use cases and pilot projects that have been applied worldwide.

Chapter 4 describes current trends in AI and the global AI market and delves deeper into the analysis of the main challenges and opportunities offered by the development and deployment of AI technology in the transportation and logistics sectors. The chapter provides an overview of existing literature related to AI applications in the transport and logistics sector, followed by an extensive description and discussion of the current and future deployment of AI in the transport and logistics sectors. The chapter also presents a detailed description of many global practical examples of AI applications in these two sectors.

Chapter 5 turns attention to the challenges, opportunities, and development of AI technology in the airport and seaport sectors. The focus is on the application of AI in port logistics activities and processes, as well as in the case of airport traffic management and airport management activities. This chapter also provides and discusses multiple use cases and pilot projects that have been executed at the European and international levels.

Chapter 6 discusses the main important challenges facing the deployment of AI technology in relation to ethics, governance, and regulation.

Chapter 7 provides concluding remarks and gives a summary of potential research topics involving the development and implementation of AI in airports and port logistics, which can be used to set up a research agenda for the Mainport logistics research group of the Amsterdam University of Applied Sciences.

The rise of AI: Global trends and developments of AI sector

2. The rise of AI: Global trends and developments of AI sector

2.1. Wat is AI?

Although the concept of Artificial Intelligence is as we understand it today, there are many examples in the history of humankind where advances in science, mathematics, and engineering enabled scientists to build the first automata engines. One example of such an invention was built by the inventor and engineer AL-Jazri who lived in the 12th century. Besides his most known inventions of automata were the famous Elephant Clock and Peacock Fountain, he built a mechanical robot that (probably) uses the sun as an energy source for his limited movements/ steps (walking forward and backward) in executing his main task of serving water by hand to humans. Another inventor of the Middle Ages was Leonardo da Vinci (15th-16th century) who designed several machines, including a flying machine and a mechanical knight. Another great invention during the 19th century was the design and partial building of two early mechanical computers (the difference engine and the analytical engine) by the British mechanical engineer Charles Babbage. The analytical engine was the first machine to have the basic elements of a computer such as a memory for storing data and instructions, a processing unit, and a control unit for managing flows of instruction. Babbage himself was not able to finish groundbreaking inventions and complete a working model due to a lack of funding and technical challenges. However, he inspired future generations of engineers and computer scientists to pursue his path and develop the first computers, which lay the basis for the development of the AI field.

It was only during the 1950s that the concept of Artificial Intelligence was coined when researchers began to explore the way to create machines that can perform tasks that would normally require human intelligence. In the 1960s, the first early AI programs were set up, including the first expert systems and natural language processing systems, and in the 1970s AI research progressed slowly because of the limited computing power and lack of data. it was only during the 1980s were the field of AI resurged as computer power increased as well as the development of advanced computer hardware and software.

Research in the areas of expert systems, robotics, and neural networks flourished significantly. From the 1900s till the 2010s, the focus has shifted to the practical application of AI such as computer vision and speech recognition, machine learning and deep learning, reinforcement learning, and language processing. AI applications become more widespread, including in fields like healthcare, finance, and transportation. Big tech companies jumped into the AI market and began to invest heavily in this new technology, especially in the development of virtual assistants, and self-driving cars, among other things.

Today AI continues to evolve more rapidly, with increased fairness and critics on explainability, ethics, fairness, and accountability. Further breakthroughs are expected in the development of fully autonomous self-learning AI systems and radical advances in quantum computing and neuromorphic computing.

Having said that, with current advancements in computing power and advanced hardware and software, Artificial intelligence (AI) is expected to lead the fifth industrial revolution that will have great impacts on various domains and activities. The power of AI technology arises from its ability to process a large amount of data very quickly, and its capability to mimic specific and valuable aspects of human intelligence, including perception, learning, reasoning, planning, and (in some cases) decision-making (McKinsey & Company., 2020., p. 5). A large part of existing AI systems, that are based on advanced neural networks and other AI algorithms, can recognize effaces, behavior, and even the motions of people through speech, can accurately translate between different languages, and can assist with decision-making (Baruffaldi et al. 2020).

At the global level, the technological race in the AI sector is in full swing, as many countries and thousands of companies and research institutes, stimulated by national governments, are working on new innovative applications for AI in practically all economic sectors and activities, ranging from agriculture, industry, services, marketing and sales, mobility, transport and logistics (MTL), security, education, healthcare, etc. Much of the activity of AI technology development is geographically concentrated around high-tech and research clusters around the world, particularly in the USA and China and to a less extent in Europe, which shows rising levels of AI development and adoption.

Global companies in industry and services use the capabilities of AI technology for creating economic, cultural, and societal values, and generating value-added that strengthen their market position and improve their competitiveness.

The development and growth of the AI sector during the last two decennia have been spectacular, even though Artificial Intelligent technologies have been developed and applied since the 1950s when Alan Turing (1950) conducted an "AI-test" where a human interrogator tried to distinguish between a computer and human text response (Turing, 1950; Haenlein and Kaplan, 2019). Since then, the evolution of AI has undergone three distinctive basic stages of development:
1). Basic AI: Is a very rudimentary and very limited in a scope AI system that can perform only one functional area (AlphaGo computer program playing the board game Go).
2). Advanced AI: Is much more advanced AI systems that integrate the power of reasoning, abstract thinking, and/or problem-solving (AI machines that have (theoretically) the ability to solve problems, learn, and plan for the future.
3). Autonomous AI: Is the final stage where AI will surpass human intelligence (e.g., the human brain) across all fields of (human) activities. This, however, is still entirely theoretical as AI researchers are at the beginning of exploring its development.

As mentioned before, the last two decades saw a very fast surge in the use of AI pushed by, among other things, the advancements in automation and digitalization of activities and processes (e.g., the digital interconnection of products, services, machines, and communication devices) that have been made possible by the fast increase in the volume and velocity of data generated by digitalized systems and the increase in processing of big data due to the availability of faster computers (computer power increased by a rough factor of 10 each year during the last 20 years). Also, the lower-cost computing power, particularly through cloud services and new models of neural networks, has dramatically increased the speed and power of AI. Finally, the algorithmic advances and the development of deep learning based on artificial neural networks and other automated machine learning techniques offered new opportunities for exploiting large amounts of data for new applications and opened new possibilities to improve the efficiency of operations, including markets, transportation and logistics, and industrial production systems (Nolan, 2020; Rammer et al., 2020., p. 1).

2.2. Definition, sub-fields, techniques and approaches

Artificial Intelligence means different things to different people. For most people, AI can be defined as the science and engineering of intelligent machines with a special focus on intelligent computer programs and mathematics.
In computer science, AI is defined from the perspective of the human approach which considers AI as systems that can think and act like humans, and from the ideal approach which considers AI as systems that can think rationally (better than humans). In other words, Artificial Intelligence (AI) refers to processes that enable systems to replace or augment specific or general human tasks and/or develop new capabilities that humans cannot perform.
More generally, AI enables systems to sense and perceive the environment, reason and analyze information, learn from experience and adapt to new situations, potentially without human interaction, and finally, make decisions, communicate, and take action.

There exist many definitions of AI. To avoid misunderstanding and achieve a shared common knowledge of AI, the European Union, has adopted the following definition:
"Artificial intelligence (AI) refers to systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy– to achieve specific goals". (European Commission, 2019., op cit., p. 5). This definition is also adopted in the government's AI Strategic Action Plan in The Netherlands.
Note that AI systems can be purely based on software (virtual world, voice assistance, image analysis software, face recognition systems, etc.) or can be embedded in hardware devices (drones, advanced robots, autonomous cars, IoT applications, etc.). Some of the most exciting, developed approaches to artificial intelligence in recent years, which drive the development of AI technology forward, are the modeling of the human brain (e.g., machine learning using neural networks), the development and application of advanced logical rules in natural language

processing, and development of advanced mathematical and statistical approaches and algorithms for object recognition and autonomous handling and decision making. Examples of AI applications include Amazon Machine Learning Services, Google DeepMind and TensorFlow, IBM Watson, and Microsoft Cortana Intelligence Suite, among others. (IFC, 2019., p.2).

The Figure 1 below gives an overview of existing AI techniques and approaches today.

Machine learning approaches	Logic- and knowledge-based approaches	Statistical approaches	Other approaches
1. Supervised learning	1. Knowledge representation	1. Bayesian estimation	1. Federated learning (data sharing)*
2. Unsupervised learning	2. Inductive (logic) programming	2. Search and optimization methods	2. Multi-Party Computation*
3. Reinforcement learning	3. Knowledge bases	3. …	3. …
4. Deep learning	4. Influence and deductive engines		
5. Federated learning (training)*	5. (symbolic) Reasoning		
6. …	6. Expert systems		
	7. …		* not mentioned in The AI Act

Figure 1. AI techniques and approaches (NL-AIC, 2021., p. 15).

The main generic aspects of AI, regardless of the application domain, are:

a). Responsible AI, which refers to the responsible handling of data/data privacy, in accordance with human norms and values, legal agreements, and ethics.

b). Explainable AI refers to the explainability of AI systems, e.g., why the AI system came to a certain decision.

c). Controllable AI refers to the design of AI systems that are controllable by humans, regardless of the degree of autonomy of the system.

d). Socially Aware AI refers to the way of interaction between AI systems and humans, by taking into consideration the cognitive capabilities of AI against humans and its impacts in the social field (for example, AI and social (ex)inclusion).

e). Data sovereignty refers to controlling and determining who, what, and when someone has access to which data, etc.

If we consider AI as a domain, then AI includes two main principal sub-fields: Machine Learning (ML) and Deep Learning (DL). Both fields are frequently mentioned in conjunction with AI algorithms that typically make predictions or classifications based on input data (see figure below).

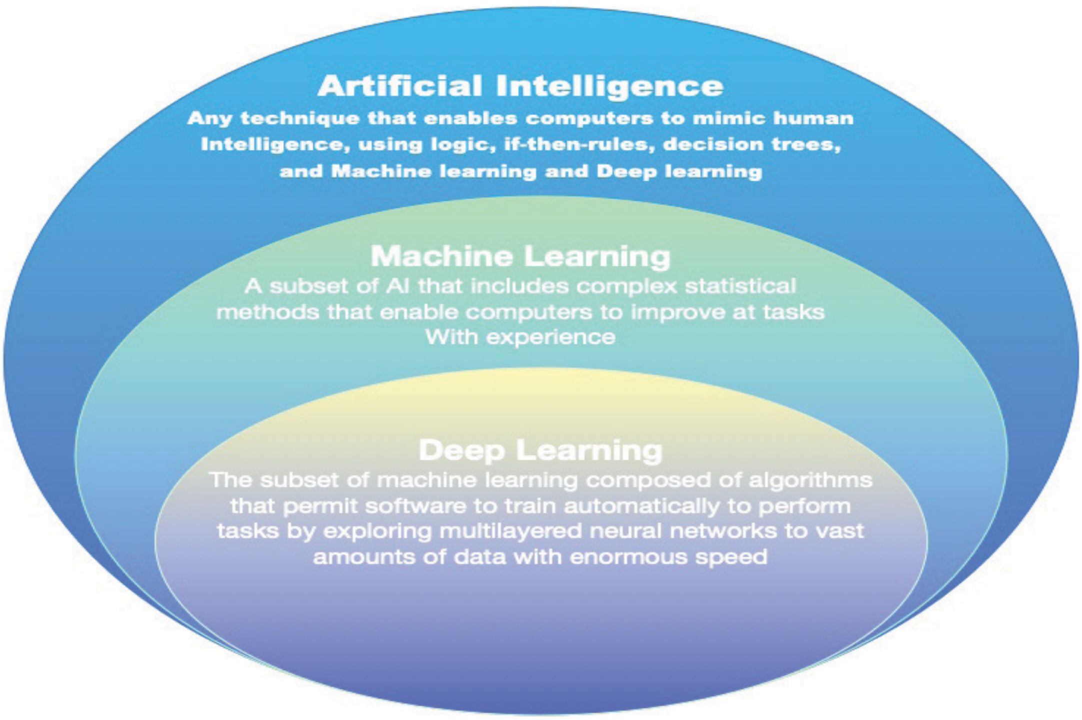

Figure 2. AI, Machine learning and deep learning.

However, the difference between deep learning and machine learning lies in the way how ML and DL algorithms learn. In machine learning, computers learn from data, discover patterns and make decisions without human intervention.

ML is broadly categorized into supervised, unsupervised, semi-supervised, and reinforcement learning. The key algorithms used in ML are support vector machine (SVM), decision trees, logistics regression, neural networks, K-means, N-Nearest, Neighbors (kNN), etc.

In opposition, Deep learning, also known as "scalable machine learning", uses unstructured large raw data and automatically (e.g., eliminates some human interventions) determines the set of features that distinguish different categories of data from one another (for example distinguishing text from/or images). Deep learning uses neural network algorithms such as convolutional neural networks (CNN) or recurrent neural networks (RNN), composed of more than three layers, including input and output layers and multiple hidden layers. Examples of such popular algorithms are regression and classification, such as linear regression, (non)probabilistic approach, sampling (unrestricted vs. restricted), Long Short-Term Memory (LSTM), Monte Carlo Sampling, Boltzmann Machines, Boltzmann Machines Learning (BML), Generative Adversarial Networks (GANs), etc.

Besides ML and DL, AI encompasses various other branches, such as expert systems, robotics, computer vision, Natural Language Processing (NLP), Planning, and many other branches of application fields. The figure below gives an overview of the main branches of the AI ecosystem.

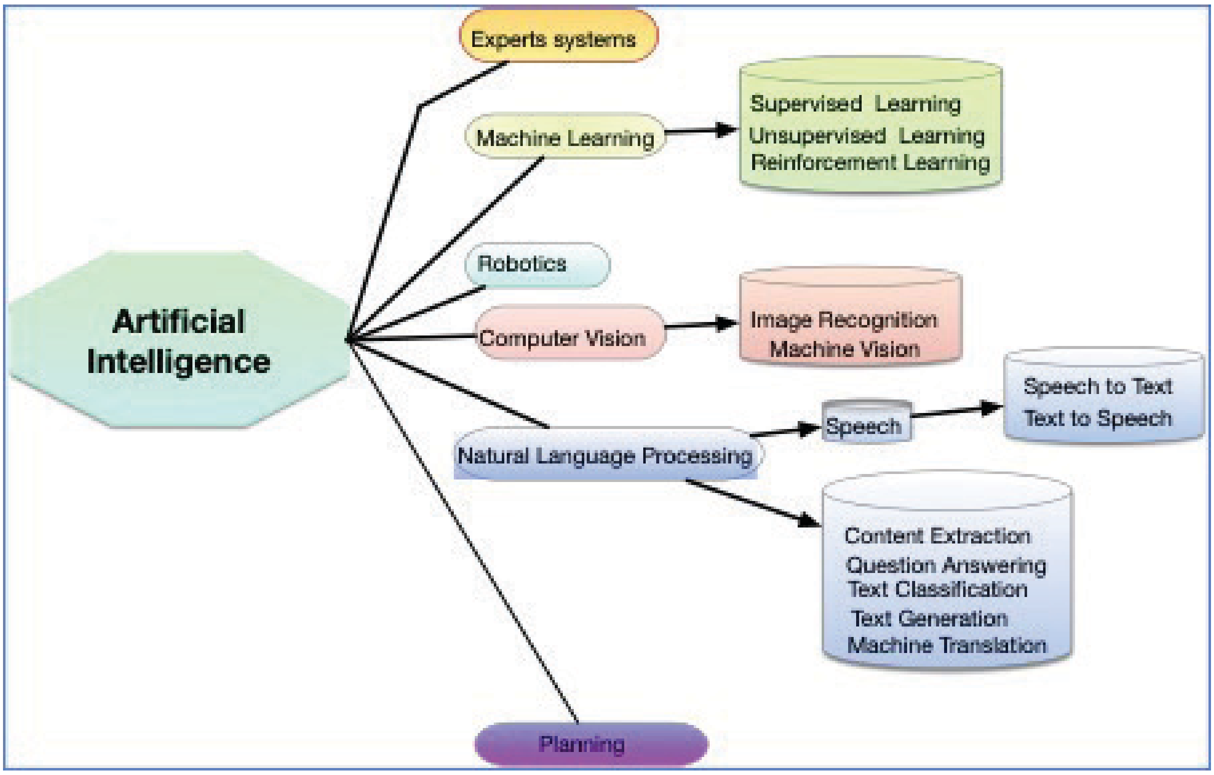

Figure 3. Main branches of AI1. Source: Author (based on literature review).

Recent advanced techniques of AI models use Generative Adversarial Networks (GANs), Diffusion models, and Transformer Models. Generative Adversarial Networks are a revolutionary framework for training massive networks without exactly having a complete set of data to do so (used in AlphaGO and OpenAI Five). However, training is hard when using these techniques, because after the network is trained, there is little to no incentive to try new things.

In the diffusion model for example, which is based on the idea of training a set by adding different levels of noise to valid real images (and their respective textual description), the learning process consists of the network learning how to remove noise in small amounts to get the final image.

In opposition to the networks that rely on conventional neural networks and recurrent neural networks, AI-driven transformer models do not require (large) labeled datasets due to their capability to find patterns mathematically.

1 Robotics is a branch of technology that is concerned with developing and training robots to interact with people and the world in general in predictable ways. However, current efforts also revolve around using deep learning to train robots to manipulate situations and act with a certain degree of self-awareness.

It is worth mentioning here that most AI algorithms used in ML and DL are applied in two phases: 1). The development phase where the gathered datasets or knowledge is used to train, test and verify the working of the algorithms, and 2). The operational or deployment phase is where the algorithms are used to (help) make decisions or predictions based on the learned knowledge within the applied model.

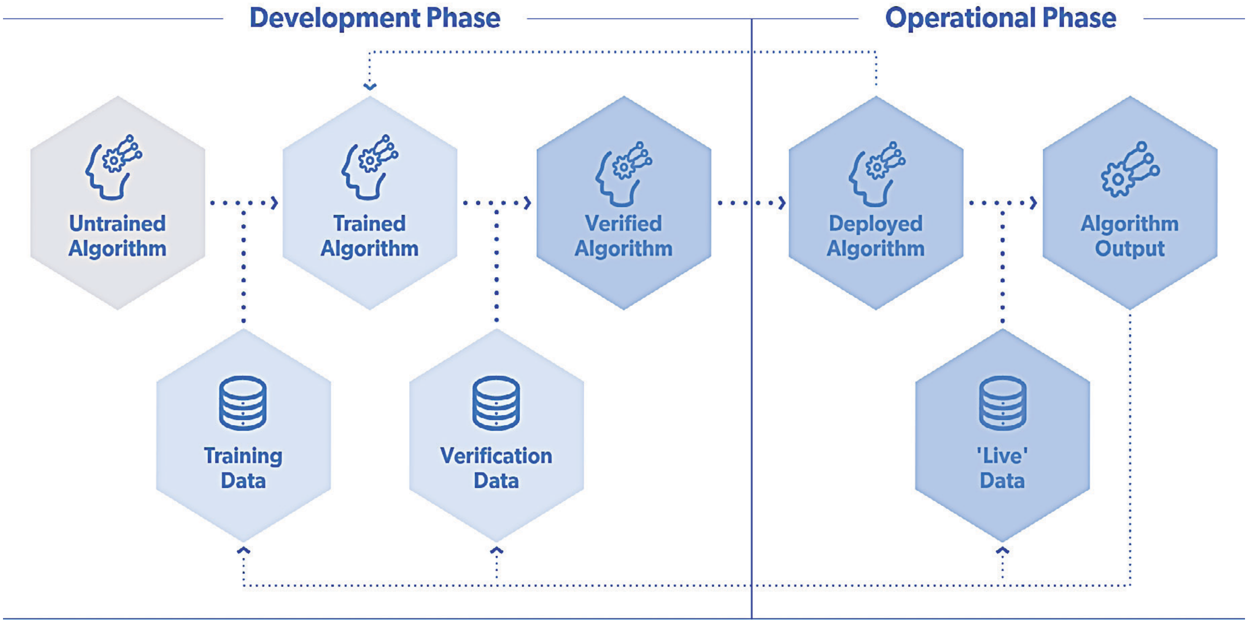

Figure 4. AI development and operational phases. Source: NL-AIC, 2021 (p. 16).

The above-mentioned AI branches and their application in industry, finance, services, education, government, healthcare, manufacturing, robotics, transport, ports and airports, logistics supply chains., etc., has great potential to stimulate economic growth, through an increase in efficiency gains at organizations and sectoral level, but also to improve the sustainability, in terms of solving environmental effects of energy and water use and greenhouse gas (GHG) emissions, and social well-being of the population.

At the organization and sector level, the adoption of AI offers many opportunities both at operational and strategic situational awareness levels. It can help to automate processes, improve the quality of operations, enhance production, etc., but can also pose challenges that might face organizations as the adoption of AI technology requires very often high amounts of investments, including the upgrade and/or full replacement of existing IT systems, and can rise challenges related to quality, compatibility, and data interoperability issues (Brock and von Wangenheim, 2019). Furthermore, the uncertainty concerning the use of AI technology in certain domains and the social and market acceptance of AI systems, especially concerning the credibility of decisions based on AI, can pose serious challenges to the successful adoption of AI. This last remark refers to the fact that the current practice of applying AI to solve real-world problems, using neural networks or other explicit AI models, lacks the ability to say much about the interpretability and the explainability of applied AI systems e.g., how the AI model structure explains its functioning and the rationale behind the decision based on learning triggered by internal processes of the system/model. In this respect, current developments in the field of explainable AI play a crucial role in mitigating the gap of interpretation and causality determination that rises with the adoption of AI systems.

The table below show sectoral applications or application domains of key AI technology.

Table 1. Application domains of AI technology.

	Computer Vision	Predictive Analytics	NLP	Data Capture/OCR
Marketing & Sales	_ Smooth user experience with visual search _ Plagiarism detection with image similarity search	_ Personalized content recommendation _ Historical data analysis on customers' activity _ Predictive sales analytics	_ Customer sentiment analysis _ Customer segmentation Audience analysis	Invoice, receipts processing
Healthcare	_ Medical imaging & disease prediction / identification _ Action recognition and fall detection for patient care _ Physical therapy and fitness with pose estimation _ Personnel authentication with face recognition	_ Medicaments demand forecasting for stockout prevention _ Inventory optimization _ Hospital personnel load prediction based on patient historical visits _ EHR patient data analytics _ Claims management _ Prior authorization	_ Data extraction for intelligent diagnostics _ Outcome prediction based on admission notes _ Analysis of unstructured data in doctor notes _ Prescriptions data analytics	Healthcare document digitisation
Sport & Wellness	_ Injury-free workouts with personalized real-time feedback to optimize physical activity _ Object tracking for players to analyse and train movements _ Automated ball tracking	Sports performance analysis	Collection and analysis of sports fan feedback in social media	Automated documents processing
E-commerce	_ Visual search of products for seamless shopping experience _ Image similarity search for higher conversion rate	_ Customer behavior analysis and demand prediction _ Competitor products analytics _ ustomer churn prediction _ Price analysis _ Inventory management	Customer sentiment analysis	Contract management Classification/ insights from invoices at scale
Retail	_ Theft and shoplifting prevention _ Personalized services to VIPs _ Employee productivity monitoring _ Product detection on retail store shelves; shelf stock-out	Historical sales data and trends analysis	_ Customer reviews collection and analyze _ Quality issues detection with product sentiment analytics	Automated data retrieval from invoices, receipts and other documents

Agriculture	_ Crop and soil health monitoring with object detection _ Crop field security _ Inventory shrinkage reduction _ Intelligent spraying & irrigation	_ Crop yield prediction _ Monitoring livestock's health and management	Customer sentiment analysis	Automated documents processing
Game & Entertainment	_ Eye tracking to improve gaming experience _ Emotion recognition for personalization _ Players movements analysis for sports or dance video games	Player churn prediction	Automated analysis of player reviews collected from forums and social media channels	-
Logistics	_ Cargo damage detection with visual inspection _ Warehouse analysis	_ Supply planning _ Demand forecasting _ Route optimization _ Freight rates prediction _ Predictive maintenance _ Sales and marketing analysis	Foreign language data cleansing and building data robustness	_ Back-office tasks automatization _ Automated documents processing
Manufacturing	_ Visual defect detection _ Forklift collision prevention _ Analog gauge data reading	_ Predictive maintenance _ Fraud detection in warranty claims	_ SOP documents search automation _ Warranty sentiment analytics	Automated documents processing
FinTech	_Unauthorized access detection and crime prevention with face recognition _ Security management	_ Anomalous transactions detection for fraud prevention _ Credit scoring for risk management _ Customer data analytics for clients retention	Customer sentiment analysis	Invoice data capture and automated documents processing
Insurance	Insurance property cost evaluation	_ Fraud claims detection Insurance claims value prediction _ High loss claims prediction	Sentiment analysis	Automated documents processing

Source: Author's compilation from various sources (2023).

2.3. Data-driven ecosystems and data sharing

With the rapid development in digitalization and automation, the volume and velocity of data gathered have increased spectacularly. Equivalently, increased demand and importance of the value of (big) data become apparent with the transition from traditional centralized data storage (owned by public and private organizations) to the emerged data platforms that require the creation of (secret) AI applications and algorithms (examples of Amazon, Facebook, Google, Alibaba, Tencent, etc.). The gathering and amassment of a high volume of data have helped to create a gigantesque business data ecosystem and data marketplace of a trillion-dollar market capitalization. These data ecosystems are built around multiple data spaces connected to network systems. An example of such a rule-based data space approach is International Data Spaces (IDS) which promotes a virtual data space to facilitate secure and standardized data exchange and data linkage in a trusted data ecosystem (IDSA., 2021., p. 29). The IDS digital ecosystem is based on a rule-based data space approach which allows companies and individuals to self-determine how, when, and at what price their data is used across the value chain. Similar data spaces are already in use in the transport and mobility sector. These data spaces provide services that combine data from all transport and mobility actors and relevant real-time transport information to enable seamless, multimodal mobility for passengers/people.

The figure below gives an overview of the composition and structure of a digital ecosystem and data space.

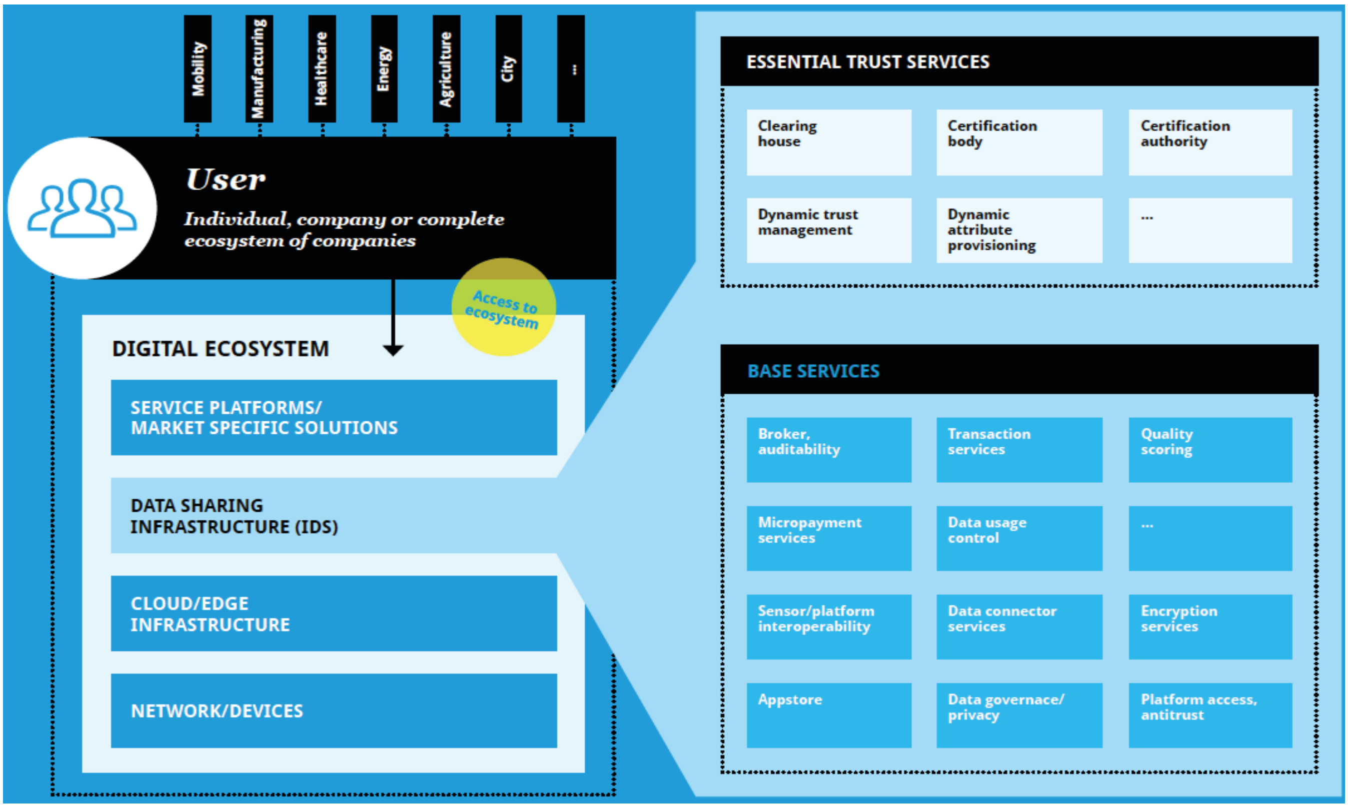

Figure 5. Rule-based data space approach of a digital ecosystem (IDSA, 2021., p. 29).

Note that most innovations of products and services emerge often from data-driven digital ecosystems. This is because they are based on inter-organizations collaboration frameworks, involving multiple parties (e.g., companies, research institutes, private and/or public entities, and customers), that jointly develop innovative solutions for the benefit of all. However, the successful implementation of such a digital ecosystem based on data space requires data sharing of different types coming from between parties, especially when developing an AI system. The ability to exchange data between parties depends on the development of seamless interconnections between intra- and inter-data spaces, which in turn depend on various aspects of interoperability, such as data formats and semantics, protocols, and interoperability of algorithms, security requirements, data sovereignty, business models and legal frameworks. Such data spaces are built on secure peer-to-peer connectivity, identity and authentication, authorization, data and data processing, and applications enabling data sharing and data exchange (NAICL, 2021., p. 27).

It is worth noting, however, that there exists a difference between data exchange and data sharing. Data exchange takes place in vertical cooperation between companies, with the aim to support and improve value chains and supply chains, while data sharing takes place in both vertical and horizontal collaboration between companies with the aim to generate additional value out of the use of data or achieve a common goal (e.g. predictive maintenance scenarios in manufacturing) (IDSA, 2019., p. 15).

Indeed, data sharing and the use of quality and reliable data are essential for the development of AI technology and building AI systems, because algorithms need big data to train the model to produce accurate predictions and/or help in decision-making. Quality of data for AI systems is essential because data is often processed from different sources with different quality levels, and the output of AI systems is very often processed by other systems.

More specifically, data used in AI systems to train the models takes place at two distinct levels: 1). Data-driven AI systems, and 2). Knowledge-driven AI systems. Data-driven AI systems learn automatically about the steps that must be taken through statistical and machine learning methods. Learning often happens using historical data, which as training data contains the relationship between properties - features - of data subjects and the resulting "outcome". In opposition, knowledge-driven AI systems are based on knowledge obtained from experts (also called knowledge elicitation) such as interviewing, case studies, and role-play. The collected knowledge can be expressed as data, for example translating "if-then" rules into mathematical functions. Both knowledge and data-driven systems process production data on which an analysis is performed for a decision or prediction.

One of the main obstacles facing the sharing of data for AI applications and models' development is the fact that the majority of existing data is privately owned and not freely available, whether by companies, individuals, public and semi-public agencies, etc. This is due to the increasing inherent value of (private) data, the costs involved in making the data suitable for AI applications, and finally, the rising concerns about safety, privacy, and control of ownership over the use of data. Other major challenges for AI deployment are related to data quality, trust (i.e., protection of sensitive data and prevention misuse), data sovereignty (i.e., exclusive decisions about the use of data), security (i.e., protecting data against unauthorized use), and collaboration standards for data sharing.

Trust is also very important to gain trust and improve confidence in adopting AI systems. Trust can be achieved by improving transparency and providing clear insights into the operation and functioning of the applied AI systems but also by eliminating any chance of bias from the use of data and/or algorithms, for example by clarifying the way machine learning is used to train data.

At the European level, data and data sharing are considered by the European Commission as key ingredients of AI development and adoption across sectors and society. The NL-AI Coalition works closely with the EU Commission in a collaborative initiative to ensure that data is Findable, Accessible, Interoperable, and Reusable (GO FAIR). Besides the IDS initiative, the EU has launched a couple of years ago the creation of the GAIA-X initiative that promotes innovation through data sharing and the development of cloud infrastructure based on a federated system that links many cloud services providers and users together. The figure below gives an overview of the structure of the data ecosystem and the underlying infrastructure.

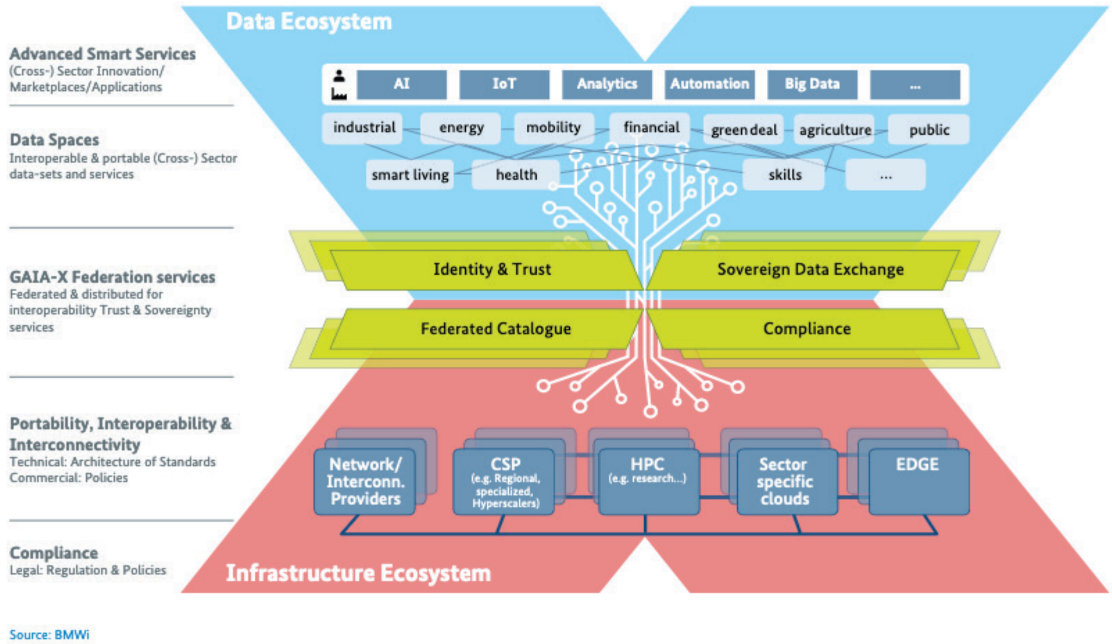

Figure 6. Structure of Gaia-X data and infrastructure ecosystem.

In The Netherlands, there is also a rapidly growing number of initiatives concerning the creation of data ecosystems based on data sharing for all kinds of applications, including AI.

A recent study on AI ecosystem and market analysis, conducted by NL-AI Coalition (2020), has identified 58 data-sharing initiatives in The Netherlands, and an important number of other AI data-sharing initiatives (mostly generic not yet mature) in development. It is estimated that the total investments in infrastructure for data sharing (e.g., in terms of venture capital raised by data infrastructure start-ups) has increased from 154 million in 2015 to 619 million in 2017 and to 1.524 billion in 2019. This reflects a growth rate of almost 900% of the data-sharing market (NL-AI Coalition, 2020., p. 19). This is in line with the global trend in global infrastructure software spending (2019) which has reached 226 billion, from which 54 billion in data infrastructure spending (2019). This growth is also reflected by the increase in the number of AI projects that are based on data sharing in The Netherlands. Examples of these projects can be found in various domains such as agriculture (IoT-based data sharing), industry (example of a project concerning the benchmarking for a trade association), finance (combatting fraud and money laundering), transport and mobility (potential value of data sharing for developing MaaS ecosystems), E-commerce (data sharing home delivery and online shopping), smart cleaning (sensor data from buildings is shared with facility management and cleaning parties), freight activities (share freight data with insurers for improved processes and better risk management), human trafficking (monitoring human trafficking through data sharing between private and public institutions), and many other domains and sectors where data sharing play a crucial role in adopting AI systems and applications.

2.4. Market development of AI: Trends and future growth

Trend analysis reports expect a surge in the development of new technologies and technological advancements that will appear in the coming decennia, including the evolution of the Internet of Things (IoT), Artificial Intelligence, Machine Learning, 5G networks, robotics, Augmented Reality (AR), Autonomous Vehicles, and the advancement in drone technology and unmanned mobility Transport.

Today, Artificial Intelligence (AI) becomes more integrated with an increasing number of domains and sectors, thanks to the adoption of new forms of digital automation, robotics, and AI-based applications in several key economic sectors, including manufacturing, logistics, agriculture, and healthcare.

At the international level, there exists a global race to fund, develop and acquire AI technologies and AI companies. The market of AI has been growing significantly since 2018 but shows high geographical concentration, in terms of investments and funding of start-up companies, registered patents, and Research and Development (R&D) activities, especially in the USA and China which are leading in AI investments worldwide. In the USA, total investments in the AI sector have increased from $10.712 million in 2018 to $16.600 million in 2019. Compared to the USA, Europe has spent much less on AI. The total investments or spending in Europe almost doubled between 2018 and 2012 (from $7 billion to $12 billion) and is projected to reach $21 billion in 2023 (IDS, Statista, 2022).

Global private investments, mainly of venture capital funds for startups (and scaleups) companies using AI, show the same tendency, with the domination of the USA showing an increase from $23.5 billion in 2020 to 63.3 billion in 2021, followed by China with an increase from $9.9 billion in 2020 to 13.1 billion in 2021), and then Europe, including UK (from $2 billion to 16.4 billion) and the rest of the world (from about $17 billion in 2020 to about 24 billion in 2021).

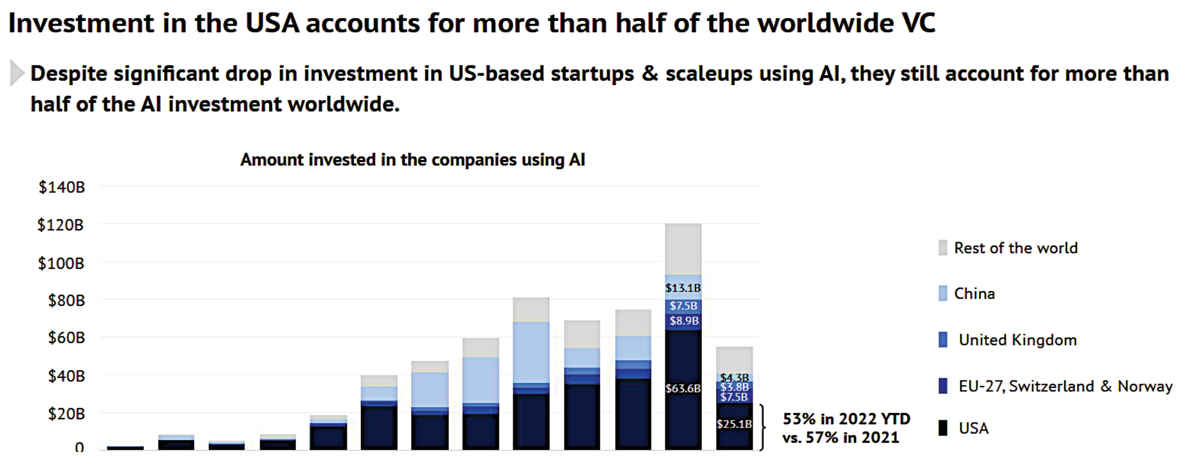

Figure 7. Total investments in companies using AI worldwide.

Source: stateof.ai (2022., p. 74).

The distribution of the total number of investments funding the startup's companies in the AI sector shows the global dominance of China in AI funding with a total of $31.7 billion during the first half of 2018, which corresponds to almost 75 percent of the global total funding of $43.5 billion (Xiaomin Mou, 2019). The largest part of these investments goes to AI companies in the fields of computer vision and imagery, machine learning (ML), natural language processing (NLP), pattern recognition, data mining, and computer-assisted instruction, and to less extent the fields of the knowledge graph, automatic translation, and personalized recommended engine.

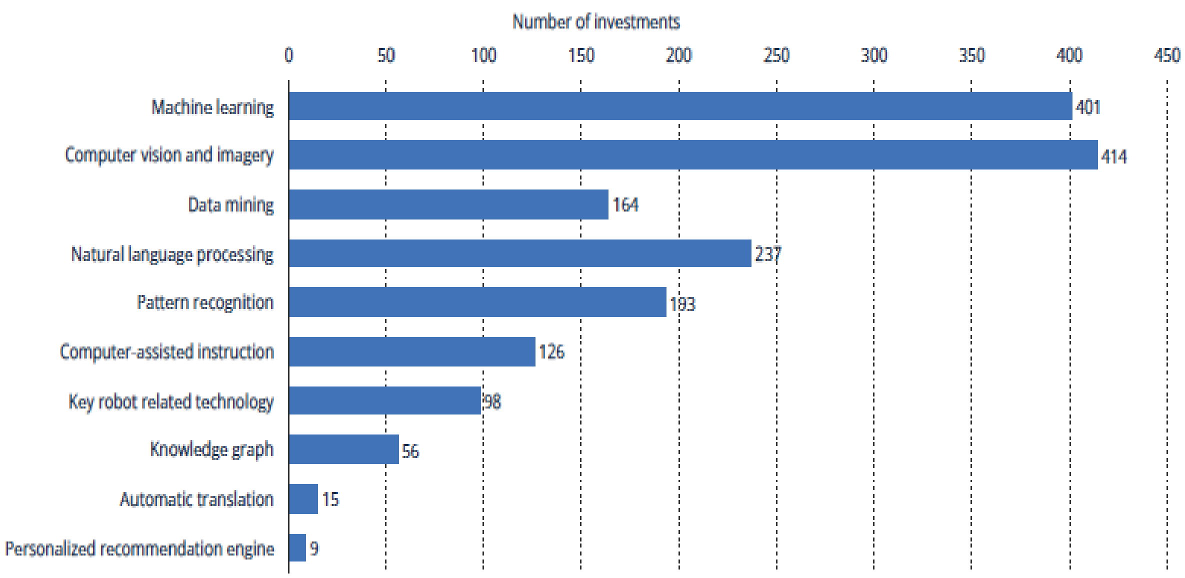

Figure 8. Investments in the artificial intelligence in China, by Segments (year 2021).

Source: Statista, 2022.

The share of AI technology applications by segment in China (2020) shows the same patterns shown by the figures concerning investments in AI in China. Indeed, AI technology is mainly applied in computer vision (29%), data mining (14%), ML (12%), intelligent speech technology (11%), NLP (6%), knowledge graph (5%), biometric recognition (4%), IC design (3%), SLAM (3%), and 1% by data labeling, computing module and expert system (Statista, 2022).

Investments are closely related to the R&D activities of AI companies, and more specifically to the number of registered or approved patents by sector and country of origin. Worldwide, the number of AI-related patents in 2021 was 30 times higher than in 2015 (141240 AI patents in 2021 against less than 5000 patents in 2015). This corresponds to a growth rate of 76.9 percent annually (AI Index report 2022., p. 36).

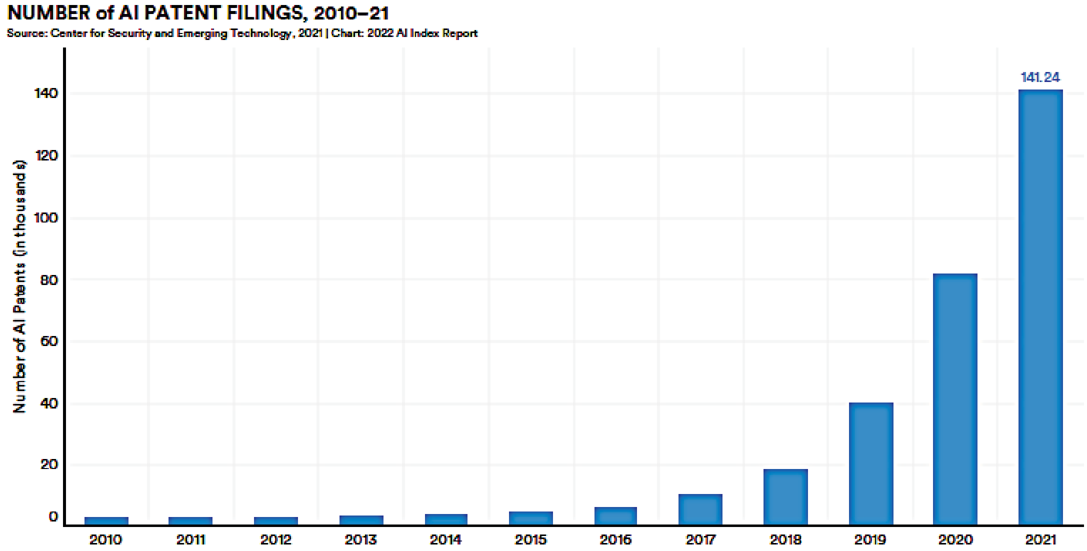

Figure 9. Number of AI patent filings worldwide between 2010 and 2021.

Source: AI Index report (2022., p. 36).

In In 2021, more than 1000 active patents in machine learning and AI were owned by Tencent (China), followed by Baidu (almost the same number of patents), and then IBM (more than 7000 patents), Samsung, and Ping An Insurance (both more than 6000 patents), and Microsoft with less than 6000 patents (Statista, 2023).

In terms of growth and revenues of the AI market, most studies show predict a market size growth of the AI sector from $ 1.21 billion in 20017 to $10.30 billion in 2030. It is estimated that the AI market will contribute by 6% to GDP gains associated with product enhancement and 4% to GDP gains associated with increased productivity in the transport and logistics sectors. In some specific markets like the transportation market, for example, AI is projected to grow at 17.87% (CAGR) between 2017 and 2030.
A study conducted by McKinsey (2021), that focuses on the use and economic potential of advanced AI techniques, shows that the adoption of AI technology can improve the economic performance of activities by128% in the travel industry, by 89% in transport and logistics, 87% in retail, 85% in automotive industry and assembly, 85% in high technology, and 79%, 67% and 57% in oil and gas, chemicals, and media and entertainment, respectively.

More generally, the global total revenues generated from the development of AI software are estimated to be $247.6 billion (2020), AI services to $ 19.7 billion, and AI hardware to $ 14.1 billion. The general expectation is that AI software revenues will grow at a CAGR of 35% worldwide in the coming years.
In 2022, the AI market revenue is estimated to be $24.9 billion in North America and $39.35 billion in China. By 2028, revenues generated from the AI market are estimated to reach $128.8 billion in North America (Statista, 2023).
At the organization level, the highest increase in revenues from the adoption of AI technology in 2020 was registered by marketing and sales (74% increase), followed by production and services development (70%), strategy and corporate finance (67%), service operations (65%), risk (64%), HR (63%), manufacturing (63%), supply chain management (54%). The average across all activities was 67% (Statista, 2022).

A study by Accenture (2022) across 16 industries estimates that AI will increase economic growth rates by a weighted average of 1,7 percent by 2035 and that companies that successfully implement AI strategies can increase their profitability by an average of 38% by 2035. The highest growth is expected to take place in information and communication (4,8%), followed by manufacturing (4,4%), financial services (4,3%), wholesale and retail, and transportation and storage (both 4%), professional services (3,8%), healthcare, construction, and agriculture (3,4%), and accommodation and food services (3,2%), Utility sector, and arts, entertainment and recreation sector (3,1% respectively), and finally, social services, public services, other services and education with an estimated increase of 2,8%, 2,3%, 1,7%, and 1,6% respectively. All percentages concern the AI steady state estimations.

In terms of Gross Value Added (GVA), this study estimates the increase in the output of the manufacturing industry between 2022-2035 of almost $4 trillion (from $8.4 to $12.2 trillion), followed by wholesale and retails by $2.2 trillion (from $6.2 to $8.4 trillion), professional services by $1.5 trillion (from $7.5 to $9.3 trillion), financial services by $1.2 trillion (from $3.4to $4.6 trillion), information and communication by $1 trillion (from $3.7 to $4.7 trillion), transportation and storage by $0.8 trillion (from $2.1 to $2.9 trillion) and construction by $0.5 trillion (from $2.8 to $3.3 trillion).

The growth in the AI market can only take place if the labor market satisfies the demand for a highly skilled workforce in the AI sector. Projections of the labor market of AI show that almost 100 million people are expected to be working in the AI sector by 2025. This means, compared to the current situation, that approximately 97 million people will be required to fill in the growing number of vacancies (job demands) in the AI sector.

Existing figures on the current global distribution of job demand for AI skills by region, based on the actual job posting, show strong demand for AI skills in Singapore, the United States, Canada, the UK, and New Zeeland.

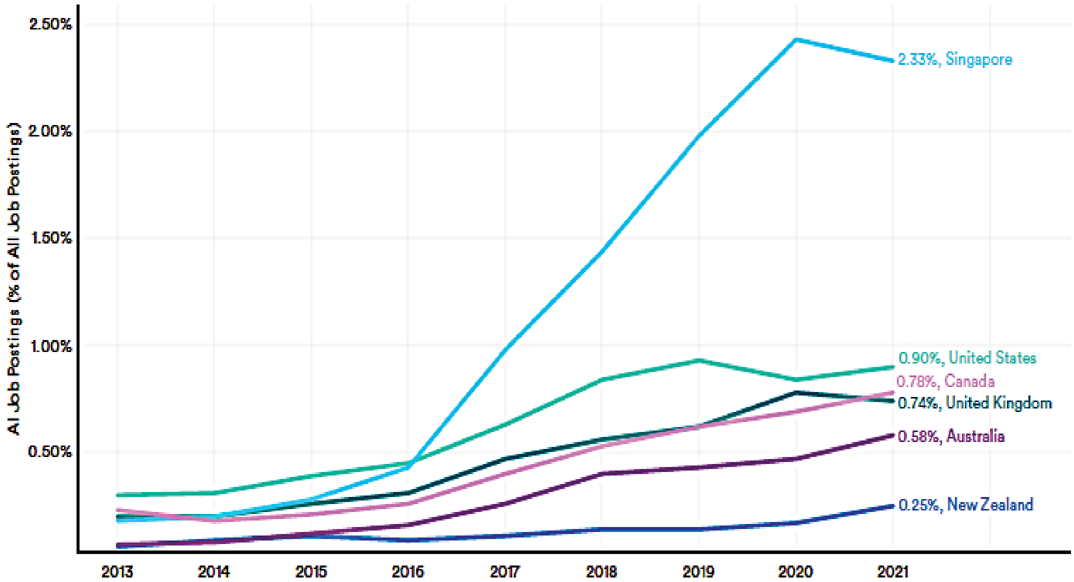

Figure 10. Current AI job postings (as % of all job postings) by countries, 2013–2021.

Source: AI Index report (2022., p. 145).

Concerning AI skill penetration rate at the international level by industry, existing data based on LinkedIn (2022) shows a strong representation of India's AI skills/workforce in education, finance, hardware software, and manufacturing, followed by the USA, Germany in those same fields, while China is ranked third and fourth in software and hardware development, respectively.

In the OECD countries, the share of employment with AI skills in 2019 was relatively small, representing only 0,3% of total employment (Green and Lamby, 2023). The highest share of employment with AI skills was found in the UK (0,47%) and Finland (0,46%), followed by countries like Sweden (0,44%), The Netherlands (0,42%), Estonia (0,41%), Austria (0,41%), Norway (0,38%), and Denmark (0,36%).

In the USA, the share of employment (in total employment) with AI skills in 2019 was higher than the average in OECD countries (0,36%). However, the distribution of AI-related labor skill demand by AI sub-fields shows a high percentage of demand in machine learning skills (0,6% of all job postings), followed by artificial intelligence (0,33%), neural networks (0,16%) and natural language processing (0,13%). The least percentages of job demand were registered for robotics, visual image recognition, and autonomous driving, with 0,11%, 01,10%, and 0,06% respectively (AI Index report, 2022., p. 146).

Finally, it is worth mentioning that concerning the potential job loss due to AI technology, it is expected that the adoption of AI will have great impacts on specific sectors and industries like wholesale, retail, transport, and storage, and lower in education, health, and social work.
According to a study conducted by PWC (2017) in the UK, on average 30% of all existing total jobs will be lost by the early 2030s because of automation and the adoption of robotics and Artificial Intelligence (AI). Some of the existing jobs will totally disappear, and other types of jobs will change in nature rather than completely disappear. The same trend in losses of existing jobs is expected in USA, Germany, and Japan, with estimated percentages of 38%, 35%, and 21% respectively.
However, there exist some variations across industry sectors concerning the (expected) magnitude and level of job losses due to AI adoption and robotic automation. It is expected for example that 56% of existing jobs will be lost in transportation and storage, about 46% in the manufacturing sector, 44% in wholesale and retail, and 37.4% in administrative and support services. The least affected sectors where the proportion of jobs loss is relatively low are education (8.5%) and domestic personnel and self-subsistence.

Fostering a digital AI ecosystem in The Netherlands

3.Fostering a digital AI ecosystem in The Netherlands

As mentioned in the introduction, NLAI Coalition (NL AIC) was founded in 2019 with the principal mission to support and stimulate the development of an AI ecosystem where public and private commercial actors can cooperate with education and research institutions, and social organizations to accelerate AI developments and adoption in the Netherlands. Its main goal is to make a substantial contribution to settle the position of The Netherlands among the European frontrunners in the knowledge and application of AI technology. To reach this goal, the Dutch government has awarded the NL-AIC and its participants 276 million (in 2021) from the so-called "National Growth Fund" as the first financing package of the multi-annual AiNed Investment Program. Consequently, various innovation hubs have been set up at the regional level to initiate regional activities leading to typical AI projects as envisaged within the NL-AIC and the AiNed investment program.

The internal structure of NL-AIC is organized into different working groups. Each working group has control over the organization, subjects, and approach, but is, at the same time, well connected to other working groups via their chairpersons and the program team. Working groups individually and collectively decide on the contents of the NL-AIC program. This program is in line with the strategic goals, as endorsed by the strategy team. The leadership of the working groups collectively forms the program team.

The strategy team consists of high-level representatives of stakeholder groups of the entire AI value chain, collaborating within NL-AIC, such as knowledge institutes (fundamental and applied research and education), government, businesses (large, medium, small, and start-up), and societal organizations and users and consumers.

Furthermore, the working groups, program team, and strategy team are operationally supported by the coalition desk in matters concerning the organization, coordination, communication (in- and external), and administration.

It is believed that the full adoption of AI in The Netherlands can lead to a 1.2% yearly growth in GDP (NLAIC, 2021).

At the national level, there exists a strong connection between NL-AI Coalition ambitions and the Top sector Logistics and the knowledge and innovation agendas (the so-called "NWA route Transport and Logistics"). At the international level, the NL-AIC also provides a dedicated linkage with the EU initiative, and cooperation exists at the level of scaling up to the European level within the Digital Europe program.

Five main themes have been identified by the NL-AI Coalition, also called building blocks, that are considered crucial for increasing the innovative impact of AI in all economic and social application areas: Data Sharing; Human Capital; Human-centered AI; Research and Innovation, and Startups and scale-ups.

1). Data sharing: The availability and access to large and relevant data are crucial for the adoption of AI technology, and AI application of machine learning and predictive power of algorithms and AI solutions in terms of accuracy and better service. Data sharing is considered a major obstacle to the development of AI systems, due to technical, legal, and commercial limitations and to diverging interests of private parties that are not always willing to share their data. In this perspective, the data-sharing working group was set up to stimulate public and private parties to share data for AI applications, by creating trusted data ecosystems (also referred to as data spaces) that can be accessed based on common agreements on data privacy and security. These data ecosystems are characterized by standardization, harmonization between other data spaces, scalability of tools and instruments, and easy set-up of data spaces for parties. Examples of such data ecosystems are Data Sharing Coalition, FAIR, and iSHARE in The Netherlands, and at the international level the already mentioned Gaia-X and IDSA data ecosystems.

2). Human Capital: attention to human capital is gaining importance as advanced AI technologies possess several characteristics that enable them to mimic human behavior and perform certain tasks more efficiently than humans. However, even though the human side of AI will always be less human than humans themselves, there is a great need to improve our knowledge of the possible societal effects of AI deployment from an ethical and human perspective. The identification and understanding of these effects can be reached by spreading knowledge, training talents, and re-training employees in the AI sector. Also, developing trust and acceptance among people can be achieved through providing free education, and learning platforms offered to individuals, sectors, and organizations.

3). Human-centered AI: the increase in the volume of data used in AI systems has increased problems related to applied AI models and algorithms that are based on these data. the main concern, in this case, is that the applied AI systems or models are not always done carefully according to a human-oriented AI approach, in which Ethical, Legal, and Societal Aspects (ELSA) is respected. Examples of such effects are the unwanted effects on democratic freedom and fundamental rights of people or groups of people in using AI systems and algorithms for identification, tracing, imaging, and predicting the behavior of humans. These effects can exacerbate when AI systems will be able to learn, act and adapt to changing circumstances independently (NL-AIC., 2020., p. 3).

One important question that can be asked when dealing with the importance of applying human-centered AI in society is the way AI technology will impact humans when it becomes an autonomous and essential factor in the decision-making process. These impacts can take place at the individual level (influence the choices, behaviors, and interpretation frameworks of individual users), at the societal level (influence the organization of the whole society), and at the social level (where the influence of AI extends to a wide variety of economic and social domains (traffic and transport, healthcare, education, etc.) (op cit., p. 3).

More generally, the development of new thinking frames/frameworks is becoming important to push AI specialists and algorithm developers to be aware and respect ethical considerations such as diversity, inclusion, well-being, fairness, justice, liability (e.g., accountability for the functioning and impact of AI systems), transparency and explainability (e.g., how AI system arrived at its conclusions), and the safety in the design and development of AI systems and applications.

Having said that, the NL-AIC has developed the so-called ELSA labs concept, in which the various parties involved (citizens, companies, knowledge institutions, and the government) in the development of the most desirable AI solutions from design to development and implementation.

4). Research and Innovation (R&D): the development of high-quality R&D infrastructure in the field of AI is considered by the NL-AI Coalition and by the Scientific Council for Government Policy (WRR) as crucial for the setup of strong foundations of the AI eco-system in The Netherlands. Today, research in the AI field is of high quality but it takes place very often on a rather limited scale and with limited new applications. This is because most new innovative solutions emerge from collaborative networks of actors (public and private) around promising research and innovation initiatives that bring new technologies to the market. However, in The Netherlands, many developed AI technologies and innovative solutions do not always reach the market.

The Dutch AI Coalition (NL AIC) is playing an important role in stimulating the Dutch organizations and companies in the AI field in increasing the opportunities to bring new technologies and innovative solutions to the market at the national level as well as at the European and global level. It also acts as a matchmaker and community builder to increase innovative breakthroughs and economic impact.

Special attention is also given to attracting and retaining talented AI experts to high-tech clusters in The Netherlands to boost the R&D activities in the AI sector.

5). Startups and Scale-up: Most innovations brought to the market are realized by Small and Medium size companies (SMEs), especially startup companies. Small startup companies are of great importance for increasing the innovation capacity of the Dutch economy because of their ability to bring innovative technology, products, and services to the market at a rapid pace. Removing barriers and blockades facing the start-ups and scale-ups for small innovative companies, whether financial, economic, and/or policy related, is important to help the county to become a global leader in the field of Artificial Intelligence. In this perspective, NL-AIC has created startups and scale-up working groups to help small companies to bring their products and services to the market and help scale up their innovative solutions. This group pays a lot of attention to international missions and events, offers solutions for better access to usuable data sets, connects startups companies and established companies to learn from each other, helps them with all kinds of legal questions, and provides financing options, training and tools for better cooperation with big high-tech companies (Actieagenda-Nederlandse-AI-Coalitie., 2018).

The building blocks presented above are organized around working groups. The role of the NL-AIC is to facilitate, stimulate, and supports the activities of these working groups that focus on the development of fundamental and practical knowledge and know-how in specific application areas such as Energy and Sustainability, Security, Peace and Justice, Technology Industry, Health and Care, Public Sector, Mobility, Agriculture, and Financial Services.

For example, the working group Mobility, Transport, and Logistics (MTL) focus on facilitating, and supporting activities related to the development and deployment of AI technology in these sectors, by adopting a collaborative network approach based on close cooperation between different stakeholders and partners within a quadruple helix framework. The group brings together various stakeholders and parties with the aim to exchange ideas, cooperate, develop, and exchange practical solutions related to the development and adoption of AI technology in transport and logistics sectors, such as 1). AI for sustainable mobility (including smart electric charging, and self-learning energy management); 2). AI for accessibility and flow (including cooperative mobility, and shared mobility); 3). AI for safe, shared, and flexible mobility (including smart self-driving vehicles, and public transport); and 4). AI for efficient logistics (including smart planning systems, predictive maintenance, and self-organizing logistics).

3.1. Innovation centres for AI in The Netherlands (ICAI)

One of many important initiatives launched by the NL-AI-Coalition is the creation of the so-called "Innovation Centres for AI" (ICAI) labs. The main purpose of the development of these ICAI labs is to connect knowledge institutes and industry partners with governmental and societal partners to develop AI technology and talents in the AI sector.

Among the many ICAIs labs created, most are in the metropolitan region of Amsterdam (MRA), such as:

1). The AI for Oncology lab, which is a collaboration between the Netherlands Cancer Institute and the University of Amsterdam. Both institutes join forces in the development of AI algorithms to improve cancer treatment, by assisting medical specialists and guiding medical interventions more accurately to the location of the tumor without damaging surrounding healthy tissue.

2). The AIM Lab (AI for Medical Imaging), which focuses on using artiKcial intelligence for medical image recognition that can help to achieve a quicker diagnosis of Alzheimer's disease, modeling cardiac rhythms, and generating automatic reports based on X-ray images.

3). The AI for Retail (AIR), which is a collaboration between UvA and Ahold Delhaize industry lab and bol.com. This lab conduct research into socially responsible algorithms that can be used to make recommendations to consumers and manage goods Wows.

4). Atlas Lab, this lab focuses on using ArtiKcial Intelligence for developing advanced, highly accurate, and safe high deKnition (HD) maps that are suitable for all levels of autonomous driving vehicles. The lab is a result of collaboration between the University of Amsterdam and TomTom,

5). The Civic ArtiKcial Intelligence Lab, this lab focuses on the development of responsible and trustworthy AI technology, more specifically on the application of artiKcial intelligence in the fields of education, welfare, environment, mobility, and health in the city of Amsterdam. The lab is a collaboration between the city of Amsterdam, the University of Amsterdam, and the VU University Amsterdam.

6). Cultural AI Lab, this lab focuses on bridges the gap between cultural heritage institutes, the humanities, and informatics, by developing and applying AI in analyzing digitized cultural collections and making them accessible to the public. Core AI research topics conducted in this lab are centered around public values such as diversity and inclusivity.

7). UvA-Bosch Delta Lab (Deep Learning Technologies Amsterdam), which is a lab that performs world-class research in machine learning and computer vision. Research conducted in this lab includes generative models, causal learning, geometric deep learning, uncertainty quantification in deep learning, human-in-the-loop methods, outlier detection, scene reconstruction, image decomposition, and semantic segmentation.

8). Discovery Lab, this lab was launched in collaboration between Elsevier, the University of Amsterdam, and VU University Amsterdam to contribute to education and science and allow Elsevier's data scientists to work closely with data scientists in academia.

9). Mercury Machine Learning Lab, the lab focuses on the development and applications of artiKcial intelligence to online travel booking and recommendation service systems. The research projects covered various topics, ranging from model-based exploration, parallel model-based reinforcement learning, methods for combined online and offline evaluation, prediction methods that correct for undesired feedback loops and selection bias, domain generalization, domain adaptation, and novel language processing models for better generalization. In this lab, the University of Amsterdam (UvA) collaborates with Delft University of Technology and Booking.com.

10). The National Police Lab AI, the main focus of this lab is on the development of AI techniques to improve safety, such as machine-learning techniques for extracting the right information from various sources (photos, text, video, etc.). In this lab, UvA collaborates with the Dutch Police, Utrecht University, and the Delft University of Technology.

11). Partnership for Online Personalized AI-driven Adaptive Radiation Therapy (POP-AART), the lab focuses on the use of artiKcial intelligence for precision radiotherapy of the tumor, by developing novel AI techniques for improving the images on which the radiation treatment is based, predicting changes over time of the tumor and incorporating them in automatic treatment planning and adaptation. In this lab, UvA collaborates with The Netherlands Cancer Institute and Elekta.

12). QUVA Lab, the lab focuses on the development and application of world-class deep vision, that allows AI systems to automatically interpret, with the aid of deep learning, what happens where, when, and why in images and video e.g., learning to recognize objects in images from a single example, personalized event detection and summarization in the video.

Besides the ICAs labs, the NL-AI-Coalition also plays important role in financing and stimulating the development of the so-called ELSA labs (Ethical, Legal, and Societal Aspects labs). In what follows, we give a brief introduction and discussion around the development of the ELSA labs in The Netherlands.

3.2. Ethical, Legal and Societal Aspects Labs (ELSA Labs)

As discussed in the previous chapter, Ethical, Legal, and Societal Aspects (ELSA) considerations become important in the development and implementation of AI technologies and systems in society. This is because the adoption and implementation of AI technology are strongly dependent on the acceptance and trust of the population and organizations, which in turn depend on the respect of rules and procedures, public values and human rights, and how the AI system is deployed (e.g., controllability) and justified (e.g., explainability). Consequently, there is a need to regulate the AI sector based on ethical, legal, and societal aspects, such as the AI systems that are used for social scoring (e.g., estimating and assessing reliability and desirable behavior through social credit systems), and the real-time biometric systems used for detection and enforcement, which can affect people in harmful ways and/or exploit people's vulnerabilities.

In this perspective, the NL-AIC has given great importance to the ethical, regulatory, and societal impacts of AI technology and applications, by proposing the concept of ELSA labs that is based on the development of human-centric AI and its different elements, including ethical guidelines for responsible AI, the legal framework (including European AI regulation) and the social shaping of technology in society.

The main idea of the ELSA labs is to bring together activities related to the ethical aspects of AI applications (e.g., connecting knowledge and practice to designing and redesigning ethics in AI and the application environment), by using a "learning community of practice" approach that focuses on participative learning in a community composed by different disciplines and focusing on real-world AI applications constructive ethics (e.g., actions that can be taken to shape AI and its applications more ethically).

In 2020, The Netherlands Organization for Scientific Research (NWO) and the NLAIC launched the NWA-Call "Human AI for an inclusive society: towards an Ecosystem of Trust". In total 5 projects were honored with the aim to start ELSA Labs that can contribute to the development of an AI ecosystem of trust. The setup of ELSA Lab is based on multiple criteria and processes aiming at enhancing a participatory and inclusive "quadruple helix" innovation environment.

The main criteria and processes on which the ELSA Labs model is based are as follows:

1). The labs focus on challenges as formulated by the Sustainable Development Goals (SDG) of the United Nations and following the research agendas for mission-driven innovation of the Dutch Top/key sectors.

2). The innovation solutions developed by the stakeholders are made available to all the ELSA lab's participants and the associated national AI ecosystem.

3). Innovation solutions are developed in a participatory, iterative, and cyclical-co-design, co-creation approach (e.g., design, development, production, testing, implementation, evaluation, etc.). In other words, ELSA's-Labs way of working is based on a collaborative approach that enables a dynamic learning process, which is essential for rapidly developing AI technology and AI systems.

4). The ELSA Lab projects must focus on meaningful and human-centric AI solutions that are based on intensive data use and AI systems.

5). The governance structure of the ELSA Labs must build on the quadruple helix governance approach (e.g., public, private, societal organizations, and research institutes), and they must have an active policy of communicating the findings transparently to stakeholders, and to the society.

6). It is the full responsibility of the ELSA Labs to scale up the developed innovation solutions and to transfer them to society.

Until 2022, the total budget invested in the development of the ELSA Labs amounts to little more than 10.9 million. Existing ELSA labs that have been financed by the NL-AIC are distributed among the military sector (defense), justice and security, culture and media, and other societal challenges.

The table below lists all existing ELSA labs and a summary of the main goals of the labs, together with information about the collaborating parties and their categorization by sector.

Table 2. ELSA Labs in The Netherlands, by domain and category (2022).

ELSA Lab	Summary	Consortium/Partners	Category
ELSA Lab Defense	Development and application of AI technology in defense (fast processing of big data and intelligent, unmanned robots, etc.). Research will focus on how AI systems and autonomous machines can be controlled by humans, as well as the development of a future-proof ecosystem for responsible use of AI in defense.	TNO, TU Delft, UL, UvA, Haagse Hogeschool, NDA, Min. Defensie, HCSS, HSD	Economy, defense, Min. of defense
AI for Multi-Agency Public Safety issues (AI-MAPS)	Public safety and security are crucial to freedom, happiness and prosperity. The aim of this ELSA Lab is the development of an ecosystem of confidence related to AI-assisted public promotion. safety. Gathering and sharing data between multiple actors, -public-private-machine agency-, play an increasingly important role in prevention, preparedness. and mitigation of damage or disaster.	EUR, TU Delft, TNO, UL, Haagse Hogeschool, Willem de Kooning Academie, Dutch Nationale Police, RASL, Civic AI Lab, Deloitte, Google, SynthO, Oditty.ai, SIDN, Nokia, Nationale Police Lab AI, UbiOps, Rathenau Instituut, PublicSonar, Woonstad Rotterdam, Dutch Police Academy, CENTRIC, HSD, Impact Coalition Safety and Security, Axis Communication, Lanner.	Economy, Domestic Administration, Justice and Security
The AI, Media and Democracy Lab	The development of theoretical models that provide insight into the dynamics of interaction within networks of strategic and learning (AI) agents. Such models can be used in the analysis of empirical data to identify and enable important control parameters that help to guide the formulation of regulations. Also, the Lab aim to develop practical tools for ethical and socially responsible design implementing AI models in practice. (e.g., developing prototypes of solutions for specific issues, but also guidelines and ethical/legal assessment frameworks).	UvA, HvA, CWI, RTL, DPG Media, NPO, Beeld en Geluid, Media Perspectives, NEMO Kennislink, Waag Society, Gemeente Amsterdam, Ministerie van BZK, Commissariaat van de Media, HU, UU Utrecht, Cultural AI Lab, KB, BBC, Bayrischer Rundfunk AI Lab.	Economy, Domestic Administration, Culture and Media

AI for Sustainable Food Systems: the AI4SFS Laboratory	This ELSA Lab aims to the development of responsible and reliable AI in sustainable food systems, including interventions, (ethical and legal) guidelines and dialogue strategies, through case studies of AI applications.	WUR, Aeres Hogeschool, Provincie Gelderland, Oost NL, Regio FoodValley, AI Hub Oost NL, FME, OnePlanet, ZLTO, FarmResult BV, ICT Campus Regio Foodvalley, Noldus Information Technology BV, VicarVision, ConnectedCare.	Other Societal Challenges
ELSA AI lab Northern Netherlands (ELSA-NN)	This ELSA AI lab will examine the cultural, ethical, legal, socio-political and psychological aspects of using AI in different decision-making contexts and integrate this knowledge into an online ELSA AI tool. The ELSA Lab contributes to healthy living, working and getting older.	UMCG, DASH, Rijksuniversiteit Groningen, Hanze Hogeschool, SterkuitArmoede, Zorgbelang Groningen, Zorgbelang Drenthe, Science LinX, Artistic Research Community in the North, Aimed, Gemeente Groningen, ZorgpleinNoord, Personalised & Connected Health (PCH) Ecosystem, Privacy1, 8Dgames, Syntho, Dhealth, Evidencio, Life Cooperative, AI hub Northern Netherlands, HANNN, University of Oxford, University of Southampton, SPRINT.	Other Societal Challenges
ELSA Lab Public Policy	This ELSA Lab aims to develop responsible and generalizable methodologies, deliver processes and prototypes for data-driven policy development. The Lab builds on existing experiments (from TNO) about the responsible application of data and machine learning for youth policy, for social issues in the transition to natural gas-free neighborhoods and for a innovation monitor that supports policymakers in making choices for innovation policy.	TNO, UL university, Hogeschool Utrecht, Hogeschool Rotterdam, ministery of Interieur and Kingdom relations, CBS, ECP.	Other Societal Challenges
ELSA Lab Smart and Responsible Mobility	The main goal of the ELSA Lab is to involving knowledge of AI and address ethical, legal and societal aspects with developers and AI researchers, governments, industry (which must deal with these developments) and citizens.	TU/E, AI-hub Brainport (including automotive industry).	Other Societal Challenges

ELSA Lab Sport Data Valley	This ELSA Lab offers citizens a digital platform for sport and training, with AI solutions that are transparent, explainable and auditable and where data privacy is guaranteed. The developed AI applications serve people and the environment and the developed innovation solutions and knowledge about practical feasibility are shared with citizens.	UL University, VU Amsterdam, HvA, TU Delft, Universiteit Twente, Amsterdam UMC, Hogeschool Utrecht, Mulier Instituut.	Other Societal Challenges

ELSA Lab Intelligent and Inclusive Urban Mobility	The aim of this ELSA Lab is the development of AI for mobility solutions in urban areas using AI-based data technology (i.e., data collection and processing and analysis) for matching demand and offer of mobility. This means that the better use of AI-driven data and information will help the providers of mobility to better respond to the behavior and wishes of the users and the public authorities with accurate information for adjusting the infrastructure needed for a good flow of urban traffic. The aim of this ELSA Lab is to develop AI applications in transport and mobility that are both legal and ethical by compiling an ELSA handbook for AI solutions in the field of urban mobility. This handbook is intended as a source of information for parties involved in improving urban mobility and developing AI solutions.	UU University and other actors from Mobility and Transport sector (not specified/known).	Other Societal Challenges
ELSA Lab Healthy Society and AI	This ELSA Lab focus on the development of human-oriented AI technology for a healthy lifestyle, by developing a toolkit, together with stakeholders, which contain a broad set of resources that can be used in the ethical, legal and societal (ELSA) challenges that come with developing such AI technology (e.g., privacy, literacy, and responsibility).	UMC Leiden University, Maastricht UMC, and other actors (not specified/known).	Other Societal Challenges

ELSA Lab Learning with AI	This ELSA Lab uses advanced and reliable AI algorithms to test the effectiveness of increase knowledge about human learning in education and in the workplace. The aim is to develop innovative AI solutions that will be deployed to support citizens and children, so that everyone can participate optimally and contribute to society. Examples are applications. that help the citizens to learn to read and products that appeal to people of all ages and backgrounds that help them to find a suitable job, and/or learning tools and assessment tools or training.	Radboud University and other actors (not specified/known).	Other Societal Challenges

ELSA Lab Meaningful Human Control over Public AI Systems	This ELSA Lab contributes to identifying realistic frameworks for human-oriented AI that must be met when applied in a government context. The focus in this Lab is on the use of AI in policy implementation as those involved in developing and implement responsible AI applications.	UL, Hague Centre for Digital Governance, TU-Delft, and other and other actors (not specified/known).	Other Societal Challenges
ELSA Lab Urban Digital Twin	This ELSA Lab will develop various innovative solutions based on urban digital twins to support municipalities and public institutions to develop better policies. The ELSA Lab therefore offers both keys enabling methodologies and the technical design of urban AI, using advanced GIS technology and techniques, Reality Capture, IoT, predictive analytics, 3D visualization, simulation and machine learning as well as other AI methods and technologies.	TU-Delft, EUR, UL University, and other actors (not specified/known).	Other Societal Challenges

	This ELSA Lab develops socially responsible data-driven solutions for the combating poverty, involving the participation of citizens and stakeholders. The ELSA Lab is aimed at people who live in poverty or are at risk of poverty (e.g., with problematic debts or threatens to get into it). The ELSA Lab ultimately aims to develop methods based on data science and AI, which, through prevention at an early stage, reduces or even reduces those first two groups as much as possible eliminates.	Maastricht University, de Open Universiteit, Zuyd Hogeschool,TNO, APG, PNA, Accenture, ministerie van Binnenlandse Zaken en Koninkrijksrelaties, Belastingdienst, KamphuisGroep, DUO,, CBS, Kredietbank Limburg, Nationale Politie, Parkstad en Gemeente Heerlen, AFM, BKR, ECP, Maatschappelijke Alliantie, NIBUD, Schuldenlab, NVB, Wijzer in geldzaken en Women Inc.	Other Societal Challenges

ELSA Lab Citizens and Society in the Energy Transition	This ELSA Lab focuses on the development of AI systems that contribute to an acceleration of the energy transition. The aims is to provide practical solutions based on AI applications that contribute to an energy system that is not only sustainable, but also fair, ethical and trustworthy.	TU Delft, and other actors (not specified/known).	Other Societal Challenges
ELSA Lab AI, Digital Culture & Media	This lab focuses on the way AI is changing digital culture and media and the underlying processes. The lab explores, in the context of a practical cases, which practical solutions are possible within the digital culture and media to people-oriented and ethical application of AI. Based on the lessons learned from practical cases, the lab will simultaneously work on overarching solutions that can contribute to a healthy digital culture with universal access, social engagement and identities community building.	UU, HU, Nederlands Instituut voor Beeld & Geluid, Public Spaces, Media Perspectives.	Other Societal Challenges
ELSA Lab AI4Access	The AI4Access Lab focuses on AI technologies that convert information into a format that is accessible to people with an auditory or visual impairment and low literacy, e.g. text-to-speech (for people with a visual disability or limited reading skills), from speech to text (for people with an auditory disability but good reading skills), or from speech to sign language (for people with a hearing impairment for whom sign language is more accessible than written text).	TU Delft, Universiteit van Amsterdam, Universiteit Leiden, Hogeschool Rotterdam, Koninklijke Bibliotheek, Beeld & Geluid, Reading and Writing Foundation, Accessibility Foundation, Foundation ABC, Probiblio, Nederlands Gebaren Centrum, Alliantie Digitaal Samenleven, Dedicon, Amberscript, Sioux Technologies, Envision, Heren van Design, Dropstuff Media B.V.	Other Societal Challenges

3.3. Practical use cases/pilots of AI applications in The Netherlands

Since 2018, a relatively high number of AI technology and systems applications, emanating from various projects, were conducted in The Netherlands and worldwide. In what follow we present and discuss in more detail the type, content, goals, parties involved, and the results of the most important use cases conducted in various application in different fields or domains.

First, in the field of data sharing, the following important pilots/use cases, emanating from ongoing or finished projects, of applied AI in The Netherlands have been identified:

1). Benchmarking for Industry Associations, this project is aiming at re-using qualified and standardized external data for financial benchmarking to support industry associations. In this project, accountants share standardized financial data with an industry association for financial benchmarking. A trusted third-party organization is designated as an intermediary that is responsible for security, authorization, and agreements around governance and metadata. The project was initiated by BR Nexus (a data-sharing initiative), and four Industry Associations (Verbond van Verzekeraars, FOCWA (a trade association for entrepreneurs in the body repair industry), Techniek Nederland, and NVL (representing Dutch leasing companies). The outcomes of the project are promising as most participants from the industry associations are satisfied with the implemented method of collecting and sharing data for benchmarking. The next step of the project is to designate a trusted intermediary for sharing aggregated data.

2). Sharing freight transport data with insurers, the aim of this project is to stimulate the implementation of digital waybills (e-CMR) in insurance claim handling. In this project, an Insured Party (IP) authorizes Insurer (I), in case of a claim, to retrieve e-CMR data at e-CMR provider to complete claim handling, using iShare blockchain technology. In transport and logistics, for example, the insured party (carrier or shipper) authorizes his Insurer to access the digital waybill (e-CMR) of a shipment when the insured party issues an insurance claim for that shipment (e.g. because of damage to the shipment). Currently, the insurer uses paper-based waybills when processing the claim for covering the damaged shipment, which is time-consuming to receive and process. For the insurer, accessing structured and machine-readable data from the e-CMR of the shipment during claim handling enables a more efficient claim handling process, as the data can be processed automatically, without manual input. The e-CMR data is controlled by the Insured Party and managed by an e-CMR provider. The data concerns at least the Shipper, the Carrier, the receiving party, the number of packages, the weight, and the (visible) condition of the goods. The main parties involved in this project are, iSHARE and Verbond van Verzekeraars (VvV).

While the first results from the pilot provide clear evidence of the potential gains of accessing e-CMR data, the insurers have not taken action to set concrete steps toward implementation. This is because insurers are not sure whether the benefits of implementing e-CMR will outweigh the expected investment costs of adoption.

3). Pilot "Weed Robot", this pilot focuses on sharing IoT data (i.e., data generated by IoT devices) to combat 'volunteer potato' (a specific type of weed) in a cost-efficient way. The underlying problem for starting the pilot is the fact that in certain crop fields, potatoes laying in a field because of crop rotation cause weeds that need to be located and sprayed with very high accuracy with pesticides, which harm other crops. The use of robots driving across the land with cameras mounted on the front (scanning) and pesticide spot sprayers on the back to combat these weeds (acting) can be the ideal solution to this problem, instead of costly manual spraying crops.

The main goal of this pilot is to integrate different, low-latency data services, into a low-latency data exchange infrastructure based on the harmonization of data services. Another objective is the ease to scale up the design of this use case to other cases that can combine scanning, analyzing, and acting data services.

The parties involved in running this pilot/use case are KPN (use of Data Services Hub), NL-AI Coalition (data sharing workgroup), AgroIntelli (a major producer of smart farming robots), and Wageningen University.

The main result from this use case was the introduction of the design plan of the pilot by KPN as part of their efforts to realize a wide range of

IoT data sharing use cases, in which scanning, analyzing, and acting data services are combined. The Weed Robot use case is a practical first step towards this end goal.

4). Pilot "Green Loans", this pilot focuses also on data sharing, particularly data retrieved from smart meters of consumers. This data is shared between Energy Distribution System Operator (DSO) and Financial Service Provider (FSP). The idea of using this data is to stimulate the greening of energy use, by delivering of green loan proposition to the consumers. The DSO can only provide this data to the Financial Service Provider when the consumers give their consent for sharing data. When consent is given, the DSO shares the monthly energy usage of the consumer from the last 13 months with the loan provider (e.g., the maximum period for which the smart meter stores data).
The main parties involved in this pilot are the HDN (Hypotheken Data Network/mortgage provider), Netbeheer Nederland (managing company of energy network), EDSN (Energy system operators, on behalf of Distribution System Operators in the Netherlands (DSO)).
In 2022, this pilot was still running and no (preliminary) results were published.

5). Pilot "Smart Cleaning", this pilot focuses on the efficient use of sensor data in buildings, more specifically data related to cleaning and facility services. The sensor data from dispensers and people counters are used to develop smart cleaning services to improve hygiene and efficiency. In this use case, a Cleaning Company uses data from sensors to determine whether soap dispensers need to be refilled and whether locations should be cleaned. The sensor provider pushes data from sensors in dispensers and people counters in batches every 5 to 15 minutes to a software supplier. The dispenser data gives information on how full a dispenser is, and the people counter shows the number of people that entered a room in the specified timeframe. The software supplier translates raw data into insights (the percentage of dispensers that need to be filled and the number of people counted during a specified timeframe) and shares these in a dashboard.
The parties involved in running this use case or pilot are the "FacilityApps" company (which develops software to enhance operational processes in cleaning and facilities), together with AMdEX. H20 (the company that resides within a building), Succes (the cleaning company), Haltian, and Ophardt ICT companies (both are sensor providers).
The results of this pilot are positive, and the cooperating parties are looking to the possibilities to expand the scope of this use case and scale up the idea to the cleaning sector and other sectors. However, issues related to access control, governance, and standardized data services need to be resolved before scaling up the pilot.

6). Pilot "Unattended Home Delivery", the pilot focuses on developing a platform for (unattended) secure home delivery. The underlying idea of this pilot project is to find a solution to data sharing through the unattended delivery solution e.g., the customer makes an order online at a merchant and selects unattended home delivery as the delivery method. The merchant assigns the delivery to a Logistic Service Provider (LSP). This last actor plans and executes the delivery to the box, and the customer retrieves the delivery from the box.
The parties involved in this pilot are "The Chain Never Stops" (offers a sustainable last mile personalized (unattended) delivery solution (TCNS)), Poort8 (offers high-quality data sharing software products), and iShare (standard and legal framework for sharing business data under control of the entitled party).
The results show that managing data access policies is essential for realizing controlled and scalable data access. Also, the most suitable solution for unattended home delivery is by implementing an Authorisation Register and developing a generic secure access hub ('the Hub') that can be used by a third party.

Second, in the field of security, peace, and justice, the following use cases of applied AI in The Netherlands are identified:
1). FIRE, the Fire project focuses on the application of AI to extract information from confiscated data by the police. Very often, in investigations of serious crimes, the police confiscate data carried in mobile phones, computers, and hard drives and used them as evidence. The manual search of this data is very costly not only in time but also money. To resolve this problem, The Netherlands Forensic Institute (NFI) has developed a self-learning algorithm that can quickly extract specific types of information from images in confiscated data carriers, including weapons or drugs on a photo, car registration plates, and even the bank account numbers on stolen passes, etc. This AI technology has been included in the

Hansken search engine (NL AIC, 2022., p. 19).

2). Trusted digital infrastructure, this project combines a data warehouse and knowledge center to improve safety in the living environment, e.g., accelerating cooperation in the chain, avoiding risks, infractions, and incidents, and detecting them more rapidly. Knowledge is extracted from the collected data using inter alia privacy-enhancing technologies, as the data is stored by the data owner (holder of the source). Various data sources are consulted to acquire new knowledge, such as the use of satellite and drone data of locations combined with public data to detect the locations of illegal activities and crimes. Companies and third parties sharing sensor data and other relevant (private) data through knowledge centers can lead to better, data-driven security of industrial sites, but also can help in setting up disaster management and preventing incidents.

3). Promising Connections, this project was initiated by the government in cooperation with the Central Agency for the Reception of Asylum Seekers (COA) with the main goal to develop an (AI) system that can help to improve the integration outcomes of asylum seekers (including labor market participation and study uptake). The project investigates how AI can help in matching the residence permit holders to a municipality where they will have the best chance of building up a new life and contributing to society. The system encompasses a digital profile of asylum seekers, that includes information about education, work experience, and ambitions.

4). Quin, this project focuses on reducing the burden of what analysts need to read in liquidation cases and track down untraceable criminals. The used AI software provides an application (Question & Investigate) for predicting the behavior of fleeing criminals. The Quin system is used by the police, public prosecution service (OM), central fine collection agency (CJIB), and the justice information service (Justid). The AI application was trained to predict the probable escape place/location where criminals will flee to or hide. Note, however, that access to sensitive data in ongoing cases presents a great obstacle toward accurate prediction of scenario escapes, for example after a ram-raid or terror threat.

5). Hansken, this project aims to increase the effectiveness and speed of investigations of criminal cases, as the volumes of data and data sources that need to be investigated in criminal cases are increasing, especially in fraud, murder, and cases of child sexual abuse materials. Hansken is a forensic search engine developed by NFI. It enables quick and efficient search (automatically structuring and indexing the data) through large numbers of confiscated data carriers such as computers and mobile phones. The AI application can search thousands of photos and images and identify anything that might be relevant for investigators, such as specific words and names or characteristics of traces such as e-mails, chat messages, or photos (taken with a specific camera or in general).
Another AI application that serves the same purposes, and is close to Hansken, is the AviaTor AI system which is used to search and detect child sexual abuse materials, including images, chat logs, geographical data, usernames, e-mail addresses, IP addresses, and audio recordings, etc., that are passed on to the police worldwide. It is a gigantic amount of material that needs investigation manually by the police. To avoid important items remaining unnoticed in that huge mountain of material, ZiuZ Visual Intelligence and Web-IQ have developed AviaTor in collaboration with a European consortium that includes the Dutch and Belgian police forces. This AI system improves the information position of investigators by mapping out the contents of large datasets of child sexual abuse materials (CSAM) and adding unique hash codes.

6). Legally and socially accepted AI in the courtroom, this project investigates how the collected data can be socially accepted as evidence in legal courts, using an AI-controlled toolkit. The requisite social acceptability is assessed in test cases, where the AI system is used to produce visualizations of the data found to assist investigators who are looking for relevant evidence. In this project, both AI software and visualization software are developed National Artificial Intelligence Police Lab, in combination with the development of a standard guideline for digital evidence and procedures for the automated production of legal evidence.

7). Policy implementation, this project aims to investigate the use of AI technology in support of risk identification, decision-making, and policy-making to enhance public and national safety and cybersecurity. There are important questions about how to use AI effectively and responsibly within the policy context, and the question about the accountability of AI systems in the public domain.

Third, in the field of media and culture, several small-scale use cases in the media and culture sector use AI technology and AI systems in targeting communication strategies. Some of them are focused on creating demonstrators to link collections of press photographs from various regional archives with digitized newspapers. Other cases focus on podcasts in which experts in AI talk with heritage and media organizations for advice about implementation and production, on developing manuals for AI production within the culture and media sectors, or on the production and distribution of best practices for the deployment of AI.
Other projects or use cases touch on various aspects of applied AI in media and culture, such as; 1). personalized and healthy media diet (GC1, 3 & 4), which makes a place where content from various providers comes together and jointly investigates what constitutes a healthy media diet. 2). Speech for culture and media (GC2), which focuses on speech recognition and speech synthesis in Dutch (make it accessible to elderly and young people); 3). Linking perspectives together across media and across time (e.g., linking historical perspective/historical data to current themes/time). 3). Making suppressed voices heard such as the project silencing the VOC Testaments, which looks for information about women and minorities in the East India Company archives. 4). Making multiple perspectives visible, such as the project focusing on information about objects in museums that are shared with the audiences through physical exhibitions and the website. 5). Predictive algorithms and how their use relates to the users (e.g., information about which material (books, newspapers, etc.) are handled in libraries can shed light on personal data such as age, sex, residential area, etc.). 6). Developing a shared vision of the legal and ethical preconditions for guiding the use of AI in culture and media.

3.3. Use cases/AI applications worldwide

At the international level, there are many AI applications in various sectors and countries. The following table gives an overview of the most important project or uses cases from the literature on applied AI technology by application domain, origin, and country. Most of these projects/use cases were published by DHL reports over the years, including the DHL report of 2022.

Table 3. Global AI applications by domain and country, 2022.

Table 3. Global AI applications by domain and country, 2022

AI Application	University/research centre	Country	Content
Zero-Waste Poultry Processing	Nanyang Technological University (NTU)	Singapore	Develop (two) processes that make use of waste, such as feathers, blood and bones, from a poultry processing facility (Collaboration with the poultry producer Leong Hup Singapore) for the production of more resilient meat storage trays and develop a cell culture medium that could be used to produce lab-grown meat. Goal: reduce the slaughter of farm animals and the impact on the environment.
Making virtual try-ons much easier	Walmart Inc.	USA	Develop virtual try-ons for helping online customers to choose their clothes (can be accessed through the Walmart app called "Be Your Own Model"). The algorithms and machine learning models used enable an ultra-realistic simulation with shadows, fabric draping and the position of clothes on people's figures.
Shopping mode for senior customers	Alibaba Group	China	The Chinese e-commerce company Taobao has developed a demographic-specific shopping mode for elderly customers (The "Elderly Mode") that offer senior customers the option to shop for medicine and groceries. The developed mode include text enlargements, voice assistants, and a simplified presentation of product information.
Decentralized Mobility Platform	DAV Network	Israel	The "Decentralized Autonomous Vehicles" is a blockchain-based mobility platform based on smart contracts that connects autonomous vehicles and drones with each other and with their customers. specific functions. Over the long term, the platform will create a connected structure of mobility and goods transport services without the need for mediating authorities. Drones could then independently seek out a charging station that is paid for automatically.
Buying e-vehicles from metaverse kiosks	1Verse Technologies Inc.	India	A partnership between the meta to real world platform 1Verse and an online retailer of automotive parts (Tyremarket.com) to sell two and three-wheel electric vehicles in the metaverse. The metaverse EV stores will reach customers who do not have easy access to physical stores. They can visit the metaverse stores via smartphones, computers and local metaverse kiosks to check out the e-vehicles, go on test rides, and make purchases.
Sensors embedded in aircraft parts	EuropäischeUnion, Aimen	Spain	The development of embedded sensors that enable real- time monitoring during flights. The 3D-printed parts are embedded in CNT fibres, where they produce data that can be used for monitoring purposes. Goals: reduce assembly costs as well as the need for the many wires used to connect sensors.

Storing CO_2 emissions from ship engines	Carbon Ridge Inc.	USA	The Carbon Ridge Inc. (start-up) is developing technology for capturing and storing carbon dioxide in the shipping industry. The modular system is connected to the vessel's exhaust funnel where it separates the CO_2 from other exhaust gases. The separated CO_2 is then sent to a container where it is compressed, liquefied for the remainder of the voyage, and then offloaded at port or on offshore terminals (A pilot project has been planned for 2023).
Circular economy for plastics	University of Illinois at Urbana-Champaign, University of California Santa Barbara, Dow Chemical	USA	Scientists and the company Dow Chemical have developed a method for economically upcycling the Polyethylene (PE) into the world's second most widely produced plastic polypropylene (PP), using a reactor and catalysts. The end product has a selectivity of more than 95% and is compatible with current industry requirements.
CO_2-neutral aviation fuel	Karlsruher Institut für Technologie (KIT)	Germany	The development of closed carbon loop for producing sustainable aviation fuel based on innovative plasma technology and scalable production process (as part of Kerogreen project). The CO_2 from ambient air is fed into various reactors where it is converted into hydrocarbons by means of a plasma generated with microwave radiation. This fuel component can then be refined into sustainable kerosene.
Automated supermarket at charging park	EnBW Energie Baden-Württemberg AG, Rewe Group, Lekkerland SE & Co. KG	Germany	The German retailer (Rewe) is opening a 24/7 automated minimart at a charging park for electric cars. The shop's supplies are tailored to the needs of users (i.e., goods for instant consumption). Consumers select their chosen items via a touch display, pay without using cash, and then receive their goods on a conveyor belt.
Battery checks using ultrasound	Oak Ridge National Laboratory (ORNL)	USA	The development of technique enabling users to check the health of operating lithium-ion batteries, using sensors (as small as a thumbnail). Ultrasound waves can continuously monitor battery material property and structural changes while the battery charges or discharges.
5G-networked construction site	TU Dresden	Germany	The development of a 5G-networked and partially automated construction site (mobile excavators, wheel loaders and a loading crane). The construction material can be located by tablet computer, AR glasses that show hidden pipes in the ground and drones that document construction progress. A transmission station for 5G-mobile communications integrated in a car trailer links all these devices in the existing network.
Compact wind turbine for roofs	AeromineTechnologies Inc.	USA	The start-up company has developed a wind turbine with no rotor blades which generates energy much more effectively than solar solutions. The compact systems can be installed in groups or individually on roofs to complement the usage possibilities of conventional wind turbines. The bladeless design uses the additional wind speed created by the vertical wall of buildings. The system is intended to complement existing rooftop PV systems.

Smart soft contact lenses	Purdue University, Indiana School of Optometry	USA	Researchers have developed a smart soft contact lens technology that can accurately measure intraocular pressure (IOP) to identify glaucoma. The tonometer on the contact lens sensor creates a wireless recording that is transmitted to a receiver in a pair of eyeglasses for daytime and when sleeping IOP measurement. The complete 24-hour IOP rhythm data can be shared with clinicians remotely via an encrypted server.
3D safeguarding system for robots	VeoRobotics Inc.	USA	The development of a 3D Safeguarding System which enables cage-free human interaction with industrial robots. The 3D safeguarding system uses dynamic speed and separation monitoring to automatically trigger a robot to stop as human co-workers move closer to the robot during operation. This allows manufacturers to improve flexibility without sacrificing reach, speed, or payloads.
Sustainable paper cup with no plastic lid	Choose Planet A Ltd.	Hong Kong	The Hong Kong-based start-up has developed and patented a paper cup, which will put an end to plastic cups. The new cup is made from bio-based and 100% certified compostable paper that is free from polyethylene. It comes with a fully integrated top flap that folds and locks into place, removing the need for a plastic lid.
AI platform helps to understand retail better	Standard Cognition Corp.	USA	The American world leading provider of retail AI (Standard AI) has developed an autonomous checkout platform that offers retailers and convenience stores the ability to understand and transform shopper behavior and in-store operations from a brand-new perspective. This platform has been enhanced by adding two powerful new tools ("Mission Control" and "Insights"), which serve to increase productivity and open up new sales possibilities.
Robotic skin feels cloth	Carnegie Mellon University	USA	Researchers from Carnegie Mellon University have developed a sensor (ReSkin) for robots, enabling them to feel and grasp layers of cloth. The touch-sensing "skin" is made of a thin, elastic polymer embedded with magnetic particles to measure three-axis tactile signals. The research team was able to achieve tactile sensing that could be used in production, for folding laundry and in household robots.
Artificial intelligence analyzes fresh produce	Neolithics	Israel	The development of software that checks fruit and vegetables on conveyor belts to reduce food waste. The artificial intelligence measures the appearance of the goods and checks whether it suits what supermarkets want in terms of look, shape, and size. The AI can also measure various nutritional parameters and pesticide levels in the fruit. The software can be seamlessly integrated into automatic sorting systems, and it provides customers with a dashboard showing the measured parameters as well as an overview of the produce's value and durability.
NFT outfits for Fashion Week	BNV.ME	France	The development of a platform/tool that enable the designer to design virtual clothes for metaverses and present them as virtual fashion collection. The fashion, which can be tailored to the individual members, is made available on a platform for metaverse fashion. This creative process enables the use of materials to be reduced significantly.
Digital twin from the DIY store	NVIDIA Corp., Lowe's Companies Inc.	USA	The US retailer has used a platform to create interactive digital twins of two stores. This enables staff to visualize digital data and interact with it to better optimize operations and meet customer needs. The virtual replicas of the physical stores combine spatial data with other data, including product location and historical order information.

Multi-camera 3D sensing for autonomous driving	Hitachi AstemoLtd.	Japan	Hitachi Astemo has developed a prototype 360-degree stereo vision system for automated vehicles, enabling them to drive on regular roads as well as highways. The system is based on a flexible multi-camera 3D sensing and is both high-resolution and highly accurate e.g., a combination of approximately 10 cameras with different angles of view, including non-parallel cameras to provide stereoscopic 3D vision.
Ethical decision-making help for AI	North Carolina State University	USA	Researchers have developed a concept, based on a devised a mathematical formula that can be used as a basis for algorithms, that will help an AI to make complex ethical decisions. The concept is a blueprint. The proposed approach has been enhanced with two mutually dependent factors and decision-making paths (i.e., the intent of a given action and the action itself) that could help the AI to perform ethically correct actions. The concept is mainly related to care-bots, but it can also be transferred to any AI application.
Sensors make rubber smart	HÜBNER GmbH & Co. KG	Germany	Based on ultrasonic sensor technology, a German company has developed the next generation in door safety and anti-trap protection systems in public transport vehicles. The SensIQ sonic system has the advantage that it is unaffected by chemical and physical influences and is therefore maintenance-free and continues to function properly even if small fissures develop.
VR-based platform for medical education	Houston Methodist Institute for Technology, Innovation and Education (MITIE)	USA	The development of a medical education app (MITIEverse™), which gives users access to customizable showcase rooms, surgical simulations and lectures from the faculty and collaborators from across the world. The VR-based platform also offers a virtual auditorium where medical professionals from around the world can give presentations. The virtual study spaces allow for global multi-user experiences with interactive models, whiteboards and other tools.
Dark store offers a new way to shop	RoofoodsLtd., Morrison Supermarkets plc	United Kingdom	The delivery service Deliveroo has opened a so-called dark store in London (is run together with the supermarket chain Morrisons), which also functions as a mini warehouse. It is a warehouse, where Deliveroo staff collect orders, and serves in the same time as a pick up point for shoppers who have ordered groceries via the app. What's more, digital kiosks have been set up at the "Deliveroo HOP" reception area to allow customers in the area to place orders. They are then handed their shopping by staff within just a few minutes, saving them the trouble of having to go into a supermarket.
Secured package room for residential properties	Position Imaging Inc.	USA	A package logistics company has developed a smart package management solution for multi-unit residential properties, office complexes, and mail centers. The "Smart Package Room" is set up in existing rooms, which are then fitted with safety and shelf systems as well as computer vision tracking. The scalable solution allows couriers to place the package on any shelf, where it will be monitored around the clock. The recipients receive a message including access data, enabling them to enter the secured area. Audio cues then guide the recipient to the package's exact location.

Tire tread scanner for mobile devices	AnylineGmbH	Austria	Anyline (an IT service company) has developed the world's first mobile tire tread scanner for cars. The app combines artificial intelligence with computer vision. It can accurately measure tire tread depth using any mobile device such as smartphones. The device scans the tire and shows the objective results about the tire tread in a matter of seconds. This solution save on hardware, training and maintenance costs for both employees and consumers.
Soap packaging made from plant waste	AlaraErtenü	Turkey	Alara Ertenü (Turkish industrial designer company) has created a waterproof soap packaging made from peapods and artichoke waste. The golden-brown is meant to be an alternative to plastic and it reduces food waste. To make the packaging, artichoke leaves and stems are freezer-dried at minus 70 degrees Celsius alongside the peapods before being pulverized into a fine powder. The powder is then mixed with water, vegetable glycerin and alginic acid. The edges are sealed using heat and the material is dyed using beetroot and turmeric.
Access to logistics robots via the web browser	ResGreenGroup International Inc	USA	ResGreen has developed a web interface that enables remote access to its monitoring tool. Logistics robots move around warehouses on magnetic tape and automate the work processes. The "Botway" monitoring tool serves as a control center for the automated fleet and can be integrated with other AMRs. The interface enables access to the system via a web browser, so that the people in charge can check and control the processes from anywhere using their phone, tablet or computer.

Source: DHL Q4 “Microtrends”. DHL Innovation Center, December 2022.

Note that all existing AI systems possess one or more of the three generic aspects described above. The application of AI systems takes place at the persons and objects level (traffic users or vehicles, airplanes, ships, containers, rail, traffic lights, etc.), or processes and systems level (policy, regulations, management infrastructure, logistics, and passenger transport, etc.).

AI applications in Transport and Logistics

4. AI applications in Transport and Logistics

As As a small country, transport and logistics are, among other sectors, the main driving force of economic growth and development of The Netherlands. At the international level, The Netherlands is considered one of the major economic centers with high-quality physical infrastructure, and highly efficient transport and logistics sectors in the world.

However, as is the case in many other European countries, transport and logistics sectors in The Netherlands face many challenges such as the increase in congestion, delays, accidents, etc., that lead to loss of time, and an increase in transport and logistics costs, as well as an increase in environmental costs. As result, many economic sectors and activities will be affected, and hence the level of economic growth, health, and well-being of the population. The development and application of AI innovation solutions might help to deal effectively with many of these challenges.

AI is one of the most rapidly evolving technologies in the transport and logistics sectors that can assist with the decision-making process and help these sectors to become more efficient, safer, and sustainable. Due to the digitalization and automation, the increase in computing power of IT systems, and the availability of enormous amounts of data collected in the fields of mobility, transport, and logistics, AI can provide adequate solutions to optimize operations, increase efficiency and efficacity processes, and significantly reduce costs by improving the planning of deliveries and more accurate forecasting and prediction of outcomes. However, the adoption of AI technology in the daily operational activities in the transport and logistics sectors depends greatly on the way organizations will deal with a combination of AI and human thinking and human interactions in solving problems. AI technology and systems can solve a lot of problems, but they are in no way a substitute for human thinking and actions, especially when decision-making depends on personal judgment, culture, norms, and beliefs.

Having said that, AI can be surely of valuable advantage in helping to solve transport problems and challenges that are related to optimizing traffic management and traffic control, modeling and predicting traffic conditions on a network-wide level, solving safety challenges in operating traffic networks, and improving interconnectivity between transport modes, and traffic and travel information to the end users (Dilmegani, 2022). On the other hand, AI can be used to solve multiple other challenges, such as accurate identification of objects and images, recognizing speech and audio, processing large amounts of data to recognize patterns, learning from experience, and adapting to new environments to predict traffic phenomena, provide situational awareness, assist drivers with maneuvering, recognize unsafe driving conditions in real-time, monitor pavement and help in support decision-making.

According to a recent position paper of TNO/TKI (2002), there exist three generic aspects of AI application in transport and logistics sectors:

a). Sensing refers to the idea of observing the world by constructing a world model based on data fusing. In transportation, the way the system communicates and interacts with other entities may pose a challenge when constructing an AI system based on sensing e.g., communication between self-driving vehicles and other vehicles, and infrastructure. Another challenge is data sharing between traffic, infrastructure, users, vehicles, and traffic rules e.g., linking ITS to traffic management data and transport and logistics data. Also, pre-processing, classifying, and labeling the shared data is crucial for developing AI systems (e.g., cleaning, filtering, fusing, and validating data for use in/by AI systems) (TNO/TKI., 2020., p. 9).

b). Thinking, refers to the capabilities of the AI system in analyzing and interpreting the observed world model and predicting future scenarios. Note, however, that in transport and logistics, many complex situations are difficult to analyze and interpret mobility policy and logistics plans. Predicting future conditions is possible if the data used in the system is sufficiently accurate and reliable. For example, with the combined use of radar images, information regarding roadworks, current traffic flows, and historical data, one might predict the occurrence of traffic jams on certain highways at a certain time (op cit., p. 10).

c). Acting, refers to the capability of the system to identify possible actions, predict the outcomes of these actions, and provide advice for decision-making, whether (acting) autonomously or supervised by humans.

Autonomously acting by AI system is not possible now, because of the ambiguities surrounding the question of how AI system can help in decision-making, by considering ethics, values, standards (formal and unwritten traffic rules), and legal frameworks (op cit., p. 11).

4.1. Literature review

Worldwide, the number of publications related to AI has increased rapidly, from 162444 publications in 2010 to 334500 publications in 2021 (Zhang ae al., 2022., p 16). This rapid increase in the number of publications was caused by the increased number of collaborations between researchers from the USA and China, and China and the UK. An important part of the produced AI academic research has resulted in practical industrial applications, leading to an annual growth rate of 76,9% in the number of AI (registered) patents since 2010.

The majority of published academic work was peer-reviewed research papers (51,5%), 21,5% were conference papers, and the rest were depositories (17%), books, book chapters, and theses (10,1%).

The highest number of AI publications were in the sub-field of pattern recognition (51690 publications), followed by machine learning (39930 pubs), computer vision (24800 pubs), algorithms (18300 pubs), data mining (15270 pubs), NLP (13430 pubs), human-computer interaction (9700 pubs), control theory (8450 pubs), and linguistic (5780 pubs) (ibid., p. 19).

In transportation studies, most AI empirical and applied research has focused on short-term flow prediction (mostly to support route optimization and traffic management flows) by using simple feedforward neural networks and/or machine learning methods.

One of the early studies in this field is the study of Ledaoux (1997) which focuses on the application of neural network systems in urban traffic flows. By using simulated data only, and by integrating a neural network system with one hidden layer into the overall urban traffic control system, the author demonstrates the possibility of predicting traffic flow for up to 1 min.

In a similar study, Dias (2001) used data from a 1,5 km section of a highway in Queensland (Australia) and applied an object-oriented neural network model with a time-lag recurrent network (TLRN) to predict short-term traffic flow. The model was able to predict future speed up to 5 min with 90-94% accuracy, and when both speed and flow were used as input to the network, the model was able to predict travel time up to 15 min with the same accuracy as speed prediction.

A most recent study by Zhou et al. (2021) presents a real-time prediction model of a situation for automated driving, using eye-tracking measures, and applying two different AI techniques (Light Gradient Boosting Machine, and SHapley Additive exPlanations). The applied model aims to better understand situation awareness that can help to design human-machine systems to optimize joint performance in conditionally automated driving. The applied model registered good performance when situation awareness is aggregated using vehicle placement, distance, and speed estimation as performance measures.

Another study on the application of the AI model to infer travel modes from GPS data (GPS trajectories) was conducted by Zhu et al. (2021). In this study, the authors propose a convolutional neural network model, using a semi-supervised federated learning (SSFL) framework to accurately identify travel modes without relying on trajectory data or data labels.

Recently, there is an increasing number of AI-based models that use real data in the areas of routing optimization, optimal route planning, and optimal transport path modeling, such as Neural Networks or intelligent routing heuristics, etc. Becker et al. (2016) for example, developed a simplified Neural Network to make routing decisions in a logistics facility. The authors tested the performance of five intelligent routing heuristics by using a real dataset from the Hamburg Harbor Car Terminal. The results of the applied AI model show that Neural Network applications outperform the best existing heuristics by a 48% increase in performance.

Hu et al. (2020) developed a machine-learning model, based on Dijkstra's algorithm, to predict a vehicle's driving conditions and speed, by considering time, distance, and other additional information (such as traffic congestion and weather condition). The empirical study was based on data of road-related information and weather information. The applied AI model was trained more than 170 times and has achieved an accuracy of 95% in predicting the vehicle's driving conditions and speed. The results show that the model can predict the conditions of traffic congestion accurately, and in doing so, it can be used to improve the effectiveness of planning the routes of delivery vehicles

In the same vein, Lakshmanaprabu et al. (2019) applied an Ant Colony Optimization (ACO) model, using real-time big data in Hadoop to the routing optimization problem. The authors show that by using big data in Hadoop in their ACO model, the processing time required by the

algorithm to solve the routing optimization can be reduced significantly.
Close to Lakshmanaprabu et al. (2019), Liu et al. (2020) applied big data, machine learning, and IoT to determine the optimal transportation path and the re-routing of massive-scale laundry services. The applied ML model predicts the demand preference of customers and supports the routing and resource allocation decision. The study demonstrates the benefit of applying AI models and techniques to enhance the efficiency of operations.

Besides a large number of existing empirical studies in the field of routing optimization, there is an important number of studies that try to tackle several challenges in the fields of traffic management and transport delays. For example, in the field of intelligent traffic systems, Kumar et al. (2021) proposed a traffic-light scheduling framework using deep reinforcement learning technique to balance the traffic flow and prevent congestion in dense areas in the city, while Lin et al. (2021), applied a high accident risk prediction model to analyze traffic accident and identify priority intersections for improvement. This study shows that road width, speed limit, and roadside markings present significant risks for traffic accidents.

In studying transport delay, using AI-based models and algorithms to predict delays, Zhang et al. (2021) constructed a collective cumulative effect prediction of train delay model to predict the arrival delays of one station in a certain period. Similarly, Wu et al. (2021) present a novel augmented machine learning approach to improve the prediction accuracy of multi-scenario real-time train delays, including regular and irregular train delays.
Similar studies were also applied in the case of airports and aviation. Most of these studies focused on flight delays and turnaround time delays at airports. For example, Chung et al. (2017) proposed a cascading neural network to predict flight delays in 112 airports, using historical flight data. The obtained results were used to feed into the optimization model, based on the Column Generation algorithm. Close to this study, Sun et al. (2020) analyzed the historical flight data regarding the relationship between departure delays to arrival delays, using a stochastic model to improve schedule reliability.
Other AI-based models were applied to predict the fuel consumption of different transport modes (train, aircraft, vehicles). In this area of AI application research, Lee et al. (2018) used the Particle Swarm Optimization (PSO) method to predict the fuel consumption function for speed optimization of voyage routing in maritime logistics. The authors estimated the net impact of voyage routes on fuel consumption by using regression analysis. The obtained results show that with the use of weather forecast data, the improvement in fuel consumption function was higher and more significant in long voyage legs. In aviation, Khan et al. (2019) applied a self-organized constructive neural network to estimate trip fuel consumption for airlines. Their study shows significant improvement in fuel consumption for airlines using the AI model.

It is worth mentioning that some of the described and presented AI-based models and techniques in this section have some limitations. One of the major critics of AI models based on neural network methods and ML is that they are considered a black box, because of the ambiguities surrounding the relationship between input (data) and the outcomes (output) and the lack of clear information about aspects of the internal architecture and computations of the applied AI systems. In addition, the development of AI-based systems or models for an efficient transportation system is very complicated, due to the creation of artificial and mechanical intelligence along with the proper understanding of human-based information and behavior. That's perhaps why, until today, AI applications in transportation are mostly limited to specific ITS applications such as data analysis and predictions of future mobility and -at least for now- less on standalone AI applications that are capable of self-handling the full range of processes.
More generally, there are good reasons to not overestimate the impact of artificial intelligence technologies nowadays or underestimate their impact in the long term. For now, artificial intelligence technology can be considered as important to accelerate evolutionary changes, and in the future maybe revolutionary changes, in the sense that it will drive businesses and organizations into radical transformations in the transport and logistics sectors (Avetisyan et al., 2020).

Finally, we conclude this section by presenting and discussing some of the existing empirical research dealing with various aspects of applied AI systems in logistics and supply chains.

According to McKinsey (2021), the implementation of AI applications in supply chain management can reduce logistics costs by 15%, inventory levels by 35%, and service levels by 65%. By adopting AI solutions into supply chain processes, logistics companies can generate $1.3 to $2 trillion per year for the next 20 years.

As presented above, the most promising application areas of AI technology in logistics and supply chains are real-time tracking and monitoring of vehicles, fuel, tires, braces, etc., smart warehousing (e.g., space optimization, management, and monitoring), smart loading and unloading, smart carrying (e.g., application of AGV, RFID, etc.), smart packaging (e.g., product design, and intelligent package products), and smart processing and distribution (e.g., intelligent sorting and labeling, intelligent management of distribution centers and the development of intelligent delivery approaches), and smart information processing (e.g., AI-based intelligent logistics information processing systems).

In recent years, a large number of empirical studies have studied the use of AI systems in these application areas.

Worschank et al. (2020) for example, conducted a systematic review of existing literature on artificial intelligence, machine learning, and deep learning that were conducted in the logistics industry. The authors identified a total number of 52.546 published papers regarding the application of AI, Machine Learning (ML), and Deep Learning (DL) in various scientific disciplines, from which they identified 103 studies in smart logistics and 148 studies in smart production. Another comprehensive literature review on the current state of applied research and methodologies related to smart technologies, including AI, in logistic operations and transportation, was conducted by Chung (2021).

Similarly, Toorajipour et al. (2021) adopted an evidence-informed, systematic literature review approach to analyze the current contributions of AI to logistics and supply chain management. Their study is based on a total of 31 articles that were identified and assigned to the field of the supply chain, from which 10 articles were devoted to logistics, and 23 articles to supply chain management. The results of this study show a mixed picture of the use of AI techniques to analyze supply chain problems. More generally, the most applied AI technique is the artificial neural network (ANN) method, while in the field of logistics, the applied AI techniques are metaheuristics and simulation frameworks, both are used to solve various combinatorial optimization problems, including automated planning systems and supply chain planning.

At the firm level, Rey et al., (2021) explored the main determinants of AI application, with a special focus on IoT adoption, in the transport and logistics sector in the region of Campania in Italy. This study shows that the level of AI adoption by companies (e.g., adoption of IoT technologies) is positively affected by the size of the firms and their Absorptive Capacity (AC). Also, the study shows that the perception of costs related to AI technology has a positive effect on the extent of AI adoption.

4.2. AI application in transportation and traffic management

As mentioned earlier, AI technology has enormous potential to address many challenges in transportation, particularly challenges related to operational processes, traffic management, safety, cybersecurity and privacy, policy and planning, travel behavior and demand, and employment and employment ethics (Nikitas, 2020, p. 8). Most people relate the application of AI technologies to connected and autonomous vehicles, such as driverless cars, platooning, drones, etc. However, the adoption of AI technology and systems in transportation extends far beyond autonomous vehicles and road infrastructure to integrate multi-modal transportation systems, including road, air, rail, and sea transport.

Currently, the most promising real-world transportation applications and deployments using AI technology and AI-based autonomous systems are Car Autonomous Vehicles (CAVs), Unmanned Aerial Vehicles (UAVs), and Personal Aerial Vehicles (PAVs), such as eVTOL (electric vertical takeoff and landing) air taxis and drones. More generally, UAVs are used in executing tasks related to intelligence, surveillance and reconnaissance, target identification and designation, counter-insurgency, attack and strike, civil security control, law enforcement applications, environmental monitoring, surveying, and geospatial activities, remote sensing, aerial mapping, weather monitoring and meteorology, forest fire detection, traffic control, cargo transport, accident reporting, emergency search and rescue, and disaster control and management.

Note that the current AI market in transport and traffic management is led by the sales of hardware and systems that allow to gather and process a large amount of real-time data (e.g., devices and sensors, outdoor cameras, automatic identifiers, digital assistance, and vehicle locators using GPS, etc.). The high volumes of data generated from the use of these devices and from vehicles are used to build efficient Intelligent Transportation Systems (ITS) and traffic management systems (TMS). These systems provide high capabilities for better planning of the transpor-

tation and logistics processes, due to information acquisition, exchange, and integration across vehicles, transport infrastructure, and other related activities. In addition, TMS systems can be made intelligent by using AI and Machine Learning to provide accurate predictions (for example, delivery time prediction solutions) and support the decision-making process for the traffic management authorities and transportation companies (e.g., transportation planning solutions). However, successful implementation of these systems depends on sharing data between different parties along the whole transport and logistics supply chains, as they compromise a set of sub-systems of transport flows and transport modes, logistics data, routing, vehicles, passengers, mapping and planning traffic information, parking management, traffic management, GPS satellite position, weather conditions, safety management and emergency, road works, reparation, maintenance, and pavement management, etc.
There exist multiple practical examples of AI applications to ITS systems, and transportation and traffic management in general.
In what follows, we present, and discuss the main application areas of AI technology and systems:
1). Autonomous and unmanned things and systems: Most traditional processes in transport and logistics are gradually being replaced by AI-based autonomous things and systems, which are becoming more prevalent and mature.
The increased adoption of these AI-based technologies and systems causes significant changes in the transport and logistics sectors. In the transport sector, the introduction of self-driving autonomous vehicles will radically change the whole transport sector in a way that has never happened in the history of the mind kind. Three radical innovative technologies are expected to lead the transition toward the future smart transport system in the coming three-four decennia:
First, self-driving autonomous vehicles; Self-driving and autonomous vehicles are slowly becoming accepted as a realistic alternative to traditional human-based manual driving. However, these self-driving vehicles need first to demonstrate that they can significantly outperform human driving capabilities. If this happens, the whole logistic system will also radically change as transport activities will become totally or less dependent on human drivers, which means less damage, risks, and accidents due to human factors, and fewer emissions and fuel usage.
The application of AI technologies in developing self-driving vehicles is based on perception (i.e., using sensors and computer vision to capture information about surroundings) as well as path planning where artificial intelligence algorithms are needed to process the incoming data and make decisions. These decisions are made based on real-time analysis of big data containing various parameters such as other road users, different types of vehicles, weather conditions, etc.
By using AI application technology and systems, autonomous vehicles can recognize objects and identify obstacles and other vehicles using the same road, interpret road signs, street markings, traffic signals, etc., and plan optimal paths considering all possible scenarios that might occur during a specific journey.
Since it is very difficult and complex to program an autonomous vehicle to react to every possible driving scenario in the real world, AI developers turn to continuous knowledge development and acquisition of deep learning in developing autonomous vehicles that can constantly improve their capabilities as they are introduced to new surroundings.
Traditional automotive industry players like BMW, Daimler, Ford, Toyota, and VW have already embraced AI as a critical component in their autonomous vehicle development strategy. New players in the Automotive market like Tesla, Google, and Waymo develop their autonomous vehicles using proprietary AI and engineering manufacturing techniques. Both global players in the automotive industry are supported in the development of autonomous vehicles by a large global network of companies such as Bosch, Mobileye, Nvidia, Quanergy, and ZF that produce traditional as well as most advanced components, including sensors, algorithms, IoT based components and devices, and data and platforms.
The figure below shows AI-based technologies and components that are needed to build self-driving autonomous vehicles and the interconnection capabilities of the vehicle with its surrounding.

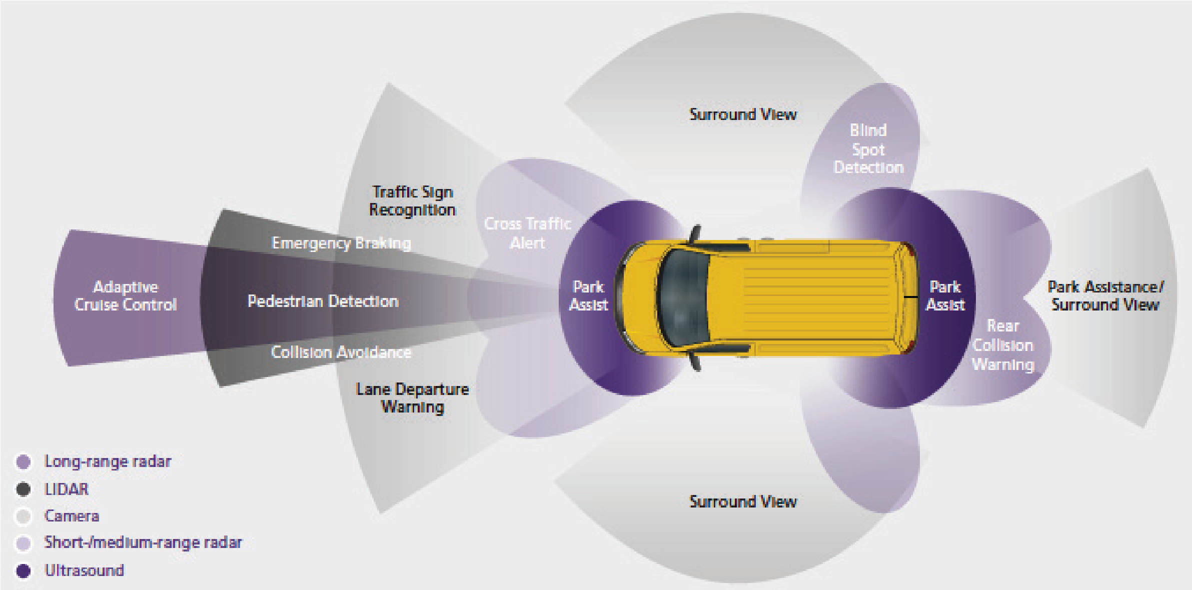

Figure 11. Sensing technologies in Autonomous Vehicles. An overview of sensing technologies present in today's autonomous vehicles; Source: DHL/IBM (2018., p. 20).

Second, the delivery drones; In logistics, delivery drones are useful in cases when products must be delivered to places that are very difficult or not possible to access due to road conditions, safety, reliability, or sustainability. Especially in the healthcare industry delivery drones can help businesses reduce transport and logistics costs and prevent investments in costly storage facilities.

Third, Unmanned Aerial Vehicles (UAVs) and Personal Aerial Vehicles (PAVs); unmanned Aerial Vehicles, including drones and unmanned aircraft systems, are used in a limited number of sectors. The development of UAVs in the transport and logistics sectors is still in the development phase. Currently, UAVs are used to support many securities and military tasks related to intelligence, surveillance, reconnaissance, border patrol, target identification and designation, counterinsurgency, attack and strike, civil security control, and law enforcement applications. They are increasingly used in civil and environmental areas such as environmental monitoring, surveying and geospatial activities, remote sensing, aerial mapping, weather monitoring and meteorology, forest fire detection, emergency search and rescue, disaster control and management, wireless coverage, cloud support, and communication relays.
However, it is expected that soon, these new transport modes will bring AI technology and wireless technologies to the aviation sector and air transport. With the improvements made in the development of high-power-density batteries, long-range and low-power micro-radio devices, cheap airframes, and powerful microprocessors and motors, UAVs have the potential to provide robust solutions for the provision of commercial transport for goods and persons (Lee and Kim, 2017., p. 9).

2). AI-based traffic management support systems, where AI is used to support decision-making to optimize the performance of multimodal transportation systems, such as the AI-powered Integrated Transportation Management System (ITMS), that include a predictive and adaptive self-monitoring transportation system (e.g., automated operations to reduce incident detection time). This type of AI system can help to predict real-time multimodal delays, due to road congestions, incidents, repair work, etc., using deep learning neural networks that can be trained using historical travel time and event data. For example, AI-based prediction algorithms can be used to estimate the optimal delivery route, and the exact travel time if transport vehicles experience unexpected or unplanned disruptions (e.g., repair work) during rush hours, and help planners to shift in time to other transport routes or other transport modes. In this case, the application of AI enables streamlining of route planning and timely delivery and can help in reducing congestion, emissions, and energy consumption, and improve travel time, planning, and on timely deliveries, thus minimizing the cost of operations and logistics costs for the companies.
More specifically, AI applications using neural networks tailored for traffic networks offer the potential to develop massive-scale and flexible models using big data that can be made available by network users. This type of AI-based traffic modeling application helps to understand and

forecast travel patterns, traffic operations, and traffic safety at a lower level of effort. This can be very helpful for transport operators, carriers, and logistics services providers because accurate and timely travel time predictions are crucial for most parties involved in the logistics chains to revise their schedule or re-configure their pre-determined delivery routes to minimize overall delays and operating costs. Various benefits can be reached by the application of AI, such as improved travel times, travel experience, dynamic pricing, and safety by providing maximum flexibility through real-time predictive and personalized travel information, less congestion, emissions, energy consumption, etc.

3). Real-time traffic management optimization and coordination, where AI is used to predict vehicles and pedestrians' arrival, queues, and delays, using a real-time traffic signal optimization system based on ML and automated traffic signal performance measures or other advanced transportation and congestion management technologies (such as centralized/decentralized AI-powered signal control systems). The adoption of such AI systems increases the efficacity and performance of traffic management and coordination systems. Also, the application of AI-based decision support systems in transport generates real-time multimodal travel information that can be customized to the need of different parties and transport modes. For example, in case of bad weather conditions and delay of one mode of transport (trains for example), travelers are given alternative door-to-door multimodal options (travel time, shortest path, etc.) along with expected delays. Thus, AI can provide highly personalized travel time information that combines multiple modes. In doing so, information from heterogeneous sources can be processed using neural networks and generated in real-time time-dependent stochastic shortest paths for every origin-destination pair.

4). Incident management, where AI is used by traffic managers to mitigate congestion by identifying the time, location, and severity of an incident. AI-based algorithms and AI systems can be used to proactively detect and predict incidents based on data from sensors, video cameras and images, CV messages, and other data sources. In this case, AI systems can process and analyze big amounts of data and images, detect patterns, and identify certain objects in the environment with high accuracy. In addition, they offer many opportunities for solving the issues related to urban network crashes and incident detection and incident management in urban areas, and managing urban traffic flows using safety metrics.

5). Asset management and maintenance, where AI is used to develop machine vision applications that can address the operation, maintenance, and improve the physical assets over their lifecycle at lower costs (US Department of Transport (DOT)., 2021).

More generally, AI applications to ITS systems result in significant improvement in efficiency, mobility, and safety, in terms of identifying and applying adequate strategies that optimize systems and economically allocate scarce resources (efficiency), improving mobility for multimodal transportation modes, reducing congestion, and recommend optimal routes using real-time data (mobility), improve incident response and prediction, and better monitoring and management of assets (safety) (Vasudevan et al., 2020).
AI functions that might be helpful in the application and adoption of AI in concrete cases in transportation are: 1). non-linear prediction application to traffic demand modeling; 2). control functions application to dynamic signal control, and route guidance; 3). pattern recognition applied to automatic detection, and image processing for traffic data collection; 4). clustering application to the identification of specific drivers based on behavior, planning application to AI-based decision support systems for transport planning, and finally, 5). optimization application to designing optimal traffic/transit networks, developing an optimal work plan for maintenance, or an optimal timing plan for a group of traffic signals (Iyer, 2021., p. 1).

4.3. AI application in logistics and supply chain solutions

In the logistics sector, artificial intelligence is seen as one of the major enablers for smart logistics and supply chains initiatives that can bring end-to-end visibility, improve the way of logistics transportation, warehousing, distribution processing, distribution, information services, reduce emissions and environmental pollution, and can contribute to time and cost savings (Song et al., 2021). Large big companies in the sector are adopting AI and machine learning as important elements to enhance real-time decision-making related to competitivity, performance, costs, inventories, asset management, and personnel, and it can also help the companies to improve resource planning systems into more advanced AI systems and analytics, semi-autonomous and fully automated (Gesing et al., 2018., p. 15). In other words, the adoption of AI technology in the logistics sector would increase the efficacity of IT systems by connecting all parties along the logistics supply chains networks and improving the logistic activities such as orders processing, consignment tracking, transport planning, asset and fleet management, inventory management, etc. However, to build an AI-based smart logistics system and make it more visible (sensing), a large amount of different types and sources of data (weather, traffic situation, traffic jams, water levels, traffic transport, planning, etc.) is needed (Prudhavi and Pai, 2022). The key to achieving this is close collaboration in sharing data between all parties along the logistics supply chains. Furthermore, clean, reliable, and validated data is crucial to the development and implementation of AI-based logistics systems.

Ideally, if the issues surrounding data sharing and interoperability of data are solved, organizations can then be able to develop sophisticated AI thinking systems, based on ML solutions, capable of dynamically predicting and forecasting future situations, providing accurate and real-time visibility of logistics operations, and providing support for better decision making.

At the strategic level, the adoption of AI systems in the logistics sector can help to manage logistics processes autonomously (i.e., acting), using robots and autonomous AI support systems (autonomous warehouses) and at the tactical level it can help to manage the planning, fleet management and maintenance of assets and equipment's, among other things.

The figure below gives a view of the relationship between AI technology components and their application to the basic functions and main constituent elements of smart logistics systems.

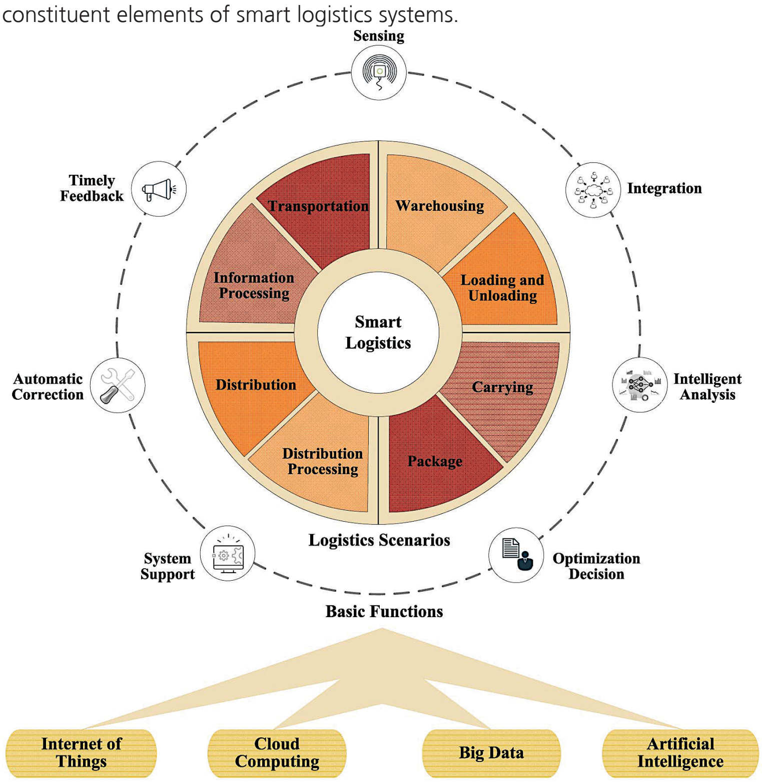

Figure 12. Basic functions of key technologies and main constituent elements of smart logistics system (Song et al., 2021, p. 4254).

There exist many logistics activities and domains where AI technology is applied to accelerate the transition towards AI-based smart logistics systems. these activities or domains range from operation management and logistics planning, warehouse management, unmanned distribution, sorting, packing, site selection, customer services, etc. Below we present and discuss the main application domains or activities of AI in the logistics sector:

1). Logistics planning: Scenario and numerical analysis, are both crucial elements of planning and fleet management e.g., position tracking systems of vehicles and goods, travel time and mileage, routing choice/route optimization, number of needed vehicles, travel costs, use of fuel, etc. The adoption of AI solutions, such as machine learning, into existing IT systems, can enhance the automation of certain facets of the logistics work and planning activities, such as order status inquiries, consignment tracking, inventory management, and order processing. By leveraging

ML technologies, Transportation Management Systems (TMS) can provide accurate recommendations tailored to customers' needs and preferences. In addition, the use of AI in planning, which combines AI's predictive analytics and advanced ML algorithms, enables companies to dynamically update supply planning parameters, and determine the most efficient route and order for stops and routes, therefore optimizing supply chain flows, minimizing drive time, fuel usage and reducing costs and emissions.

2). Intelligent Route Optimization: Route optimization is critical for transport and logistics operators, from the pickup of the shipments up to the last mile. It is estimated that the last-mile delivery process accounts for up to 28% of total transportation costs. However, even though logistics providers have deep knowledge of last-mile logistics, new customer demands such as time-slot deliveries, ad-hoc pickups, and instant delivery are creating multiple challenges even with the use of sophisticated intelligent route optimization (DHL/IBM., 2018., p. 26). The application of AI in route optimization, which combines artificial intelligence modeling with fleet management optimization, can help logistics companies to improve the overall delivery runs (e.g., faster delivery), by taking the best possible route, while avoiding congestions on roads by using real-time dynamic adjustment data based on demand fluctuations across locations. This allows companies to reduce travel costs and speed up the logistics processes and at the same time better utilization of vehicles fleet, and efficient allocation of resources. Furthermore, with improved accuracy in demand prediction, the companies can reduce operational costs significantly by optimizing the number of dispatched vehicles to loading/unloading locations and warehouses and improving manpower planning. This will result in a significant reduction in holding costs while increasing customer satisfaction.

3). Predictive Logistics: Predictive demand and planning are hardly needed in the transport and logistics sectors, and both are characterized by uncertainty and volatility. AI can help to radically shift logistics operations and processes to proactive dynamic operations using predictive intelligence, especially the use of predictive modeling of the optimal time of delivery for last-mile logistics.
This is very important to realize sustainability goals of reducing environmental effects from transport and logistics activities, which can be achieved by combining artificial intelligence modeling with deliveries scheduler and route planning optimization to predict the probability of delivery success as a function of various inputs such as time, region, address, weekday, vehicle, weather, building type, parking difficulty, etc. The predictive models then optimize routes and ordering of the deliveries to ensure that the driver delivers the order at the right time and the exact place.
Another example of predictive logistics is the predictive network management using AI modeling techniques to enhance the performance of logistics operations for freight transport, such as freight transit time delays. DHL/IBM (2018) applied such predictive modeling techniques to air freight transportation to predict if the average daily transit time for a given lane is expected to rise or fall up to a week in advance. The objective was to help air freight forwarders plan their shipments by removing subjective guesswork around when or with which airline will handle them. The developed model was able to identify the top factors influencing shipment delays, including temporal factors like departure day or operational factors such as airline on-time performance.
The same AI application and modeling techniques can be applied in predictive risk management of logistics supply chains in the automotive industry or engineering and manufacturing industries, where multiple components from thousands of suppliers worldwide are managed on daily basis (op cit., p. 26).

4). Automated warehouses and warehouse management: According to MHI/Deloitte (2020), only 12% of businesses are using AI technology in their warehouses. This percentage will reach 60% by 2026. The low number of fully AI-based automated warehouses is the very high investment costs in building new warehouses and implementing AI technology and new advanced AI systems.
The AI-based automated warehouse has many advantages in helping companies to fully exploit real-time data for predictive modeling, and tracking, managing, and monitoring inventories through each step in the transportation and delivery process. This reduces significantly the costs related to human errors and increases speed and accuracy when picking orders, which consequently, increases customer satisfaction rates and hence, business revenue.
The application of AI for automated classification and identification of goods stored in warehouses and for monitoring current inventory levels

requires AI models to be trained with data collected from previous pickings by employees based on barcodes or RFID tags attached to products. Algorithms can identify these items using computer vision while taking into account information such as product dimensions, weight, etc. (Draganjac et al., 2016).

For instance, the application of machine learning facilitates the adjustment of stocking levels to actual demand and avoids all forms of overstocking or shortages. Also, the use of predictive modeling in improving stock management and distribution solutions allows real-time predictions, through predictive analytics, and increase the chances to achieve more accurate demand forecasting than traditional statistical methods. Furthermore, AI solutions to warehouse automation, coupled with image recognition, help to increase safety and to identify suspicious acts such as unauthorized entry or work interruption.

With the expected increase in the growth rate of the warehouse robotic market by 14% (GAGR) between 2021-2026 (the global market is valued at $ 4.7 billion in 2021), it is expected that classification and management of goods/items in warehouses can be autonomously done by AI technology, robots and intelligent algorithms in combination with IoT, big data, and cloud computing.

Worldwide, there exist already several fully automated warehouses of big multinational companies, where robots using AI technology manage all warehouse operations and processes. For example, Amazon has 200.000 robots working in their warehouses distributed between 26 fulfillment centers (from a total of 175 Amazon centers), where robots are used to help workers in picking, sorting, transporting, and stowing packages. The use of AI algorithms allows real-time collaboration between AGVs, enabling optimized navigation path planning, zoning, and speeds, as well as self-learning to improve AGV capabilities over time.

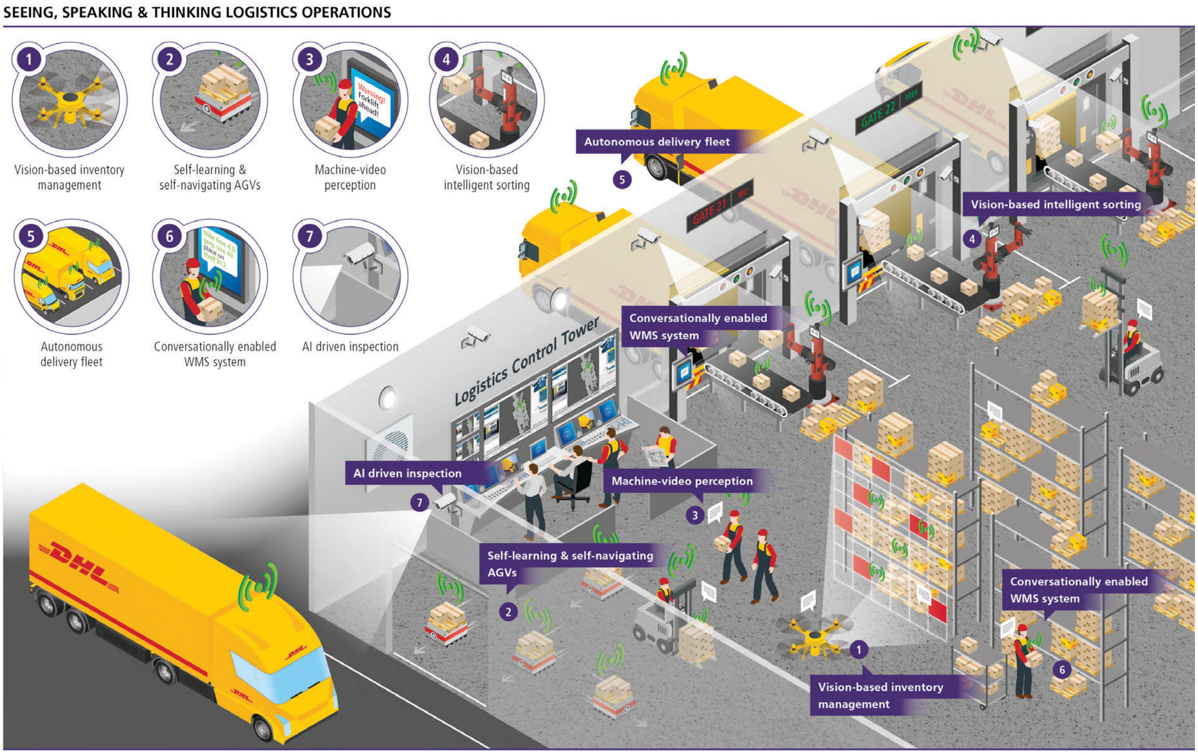

Figure 13. Seeing, speaking and thinking logistics operations.

Source: DHL/IBM (2018., p. 31).

The use of drones and AI-based computer vision technology will enable companies to conduct a visual inspection and detect damages, including depth and type of damages, and resolve it. Also, AI can be applied in warehouses to improve predictive maintenance of equipment using data collected from different sensors without being directly connected. Machine learning-powered analytics tools enhance predictive analytics and identify patterns in sensor data so that technicians can act before the failure occurs. This will help companies in reducing the costs associated with downtime and failures of assets, devices, and equipment.

5. Data analytics: Data collection, classification, analysis, and application of predictive intelligence analytical tools, whether through synchronization with AI platforms or not, become more and more standardized into businesses' IT systems. The enormous amount of data gathered in

the logistics sector is of great value to predict demand and improve the visibility of the logistics supply chain. The large volume of historical and transactional data is very useful in conducting advanced analytics to identify patterns and predict the future.

As mentioned before, logistics companies apply AI-based data analytics applications in planning/route optimization, freight management, predictive maintenance, and in dynamic pricing. For example, the sales and marketing departments of logistics companies use machine learning algorithms to enable them to analyze customer's behavior and predict demand, based on historical data and in real-time, so that they can respond in real-time to changes in demand, supply, competition price, and subsidiary product prices.

Regarding route optimization and freight management, Applied AI models are put into action to find the most efficient route for vehicles. AI web-based traffic platforms play a key role in providing real-time information about road conditions, road works, weather conditions, and congestion to users (transport companies, carriers, and logistics service companies).

In the area of fleet management, for example, fleet managers can leverage AI to increase competitiveness, enhance efficiencies in the use of the existing fleet, and decrease the costs of maintenance. With the application of intelligent sensors, companies can keep track of shipments, driving times, number of stops, driver's habits, time of picking up and returning, and technical conditions of vehicles. The data gathered through intelligent sensors can be processed by an AI system to streamline the maintenance schedules to avoid vehicle breakdown and establish smooth-running fleet management.

In the area of inventory and yield optimization, AI data analytics models can help companies to maximize efficiency and boost revenues by identifying and predicting areas of inventory that are (will) performing well and which ones are (will) not.

6). Back Office AI: Most current back-office processes and tasks in logistics companies are still done manually (e.g., invoice/bill of loading documents, delivery documents of products, etc.). However, there is a clear increase in digitalizing back-office processes, using for example automated document processing and digital exchange of documents between the partners in the logistics supply chains. Furthermore, and beyond the simple digitalization and automatization, logistics companies are also using intelligent business process automation that combines AI, robotic process automation (RPA), process mining, and other technologies to further automate back-office tasks. These hyper-automation technologies are applied in scheduling and trucking (e.g., scheduling transportation, organizing pipelines for cargo, assigning and managing employees to gates/stations, truck packages in the warehouse, etc.), report generation (e.g., using RPA tools to auto-generate regular reports to inform managers and relevant stakeholders), and email processing (e.g., based on RPA reports, RPA bots can analyze the content and send emails to relevant stakeholders).

It is worth mentioning that there is a difference between RPA automation and AI. RPA refers to systems based on rules that help to increase accuracy and speed while reducing human errors (filling in forms, copying data from one system to another, etc.), while AI is intelligent systems that can sense, interact with humans and learn from human decisions, and help in decision making.

RPA systems use ML algorithms that are capable of understanding instructions given by humans via a graphical interface or any other type of electronic data processing system, including customer relationship management (CRM) and Enterprise resource planning (ERP).

The figure below shows the difference between these two complementary systems and their interaction in supporting back-office processes.

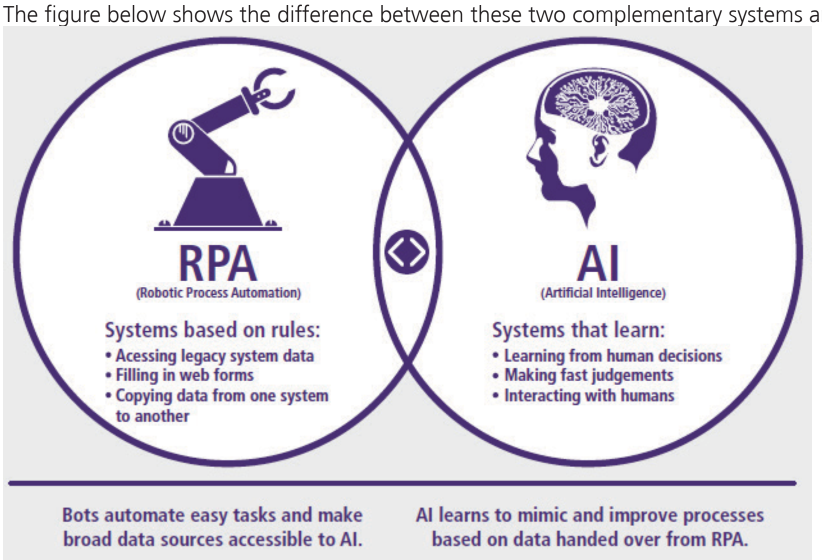

Figure 14. A comparison of RPA and AI.

Source: Boston Consulting Group (op cit., DHL/IBM, 2018., p. 22).

Finally, current trends in logistics (growth in E-commerce, last mile logistics, sustainability issues, etc.), customers and consumers except for high-quality services, speed, accuracy (on-time delivery), and more transparency (real-time tracking and updated estimates of delivery time) in the delivery process. Online shopping experiences have much AI in the background e.g., AI-driven recommendations are a powerful business driver nowadays. Most large-scale companies are using customer service AI-based chatbots (speech recognition technology) to assist human operators in quickly searching and matching the need and demands of the consumers. These chatbots are capable of handling delivery requests, taking orders, trucking shipments, and responding to FAQs (i.e., low-to-medium call-center tasks). Furthermore, chatbots are very useful in analyzing customer experience and providing analytics metrics that enable businesses to better understand customer's demand and their behavior.

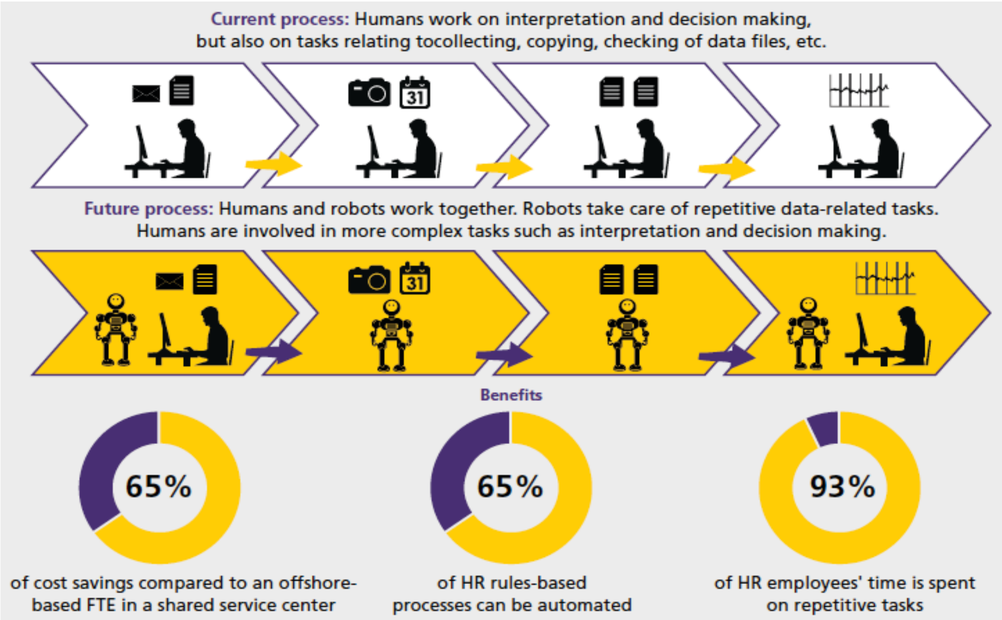

Figure 15. RPA supporting back-office processes (DHL/IBM, 2018., p. 23).

4.3.1. Examples of practical AI applications in logistics

1). Automating order picking using AI: Order picking is considered one of the most labor-intensive operations in logistics. To reduce manual operations in the order-picking process and improve autonomous decision-making, a Dutch company (Fizyr), producing robots, developed an innovative solution to identifying, analyzing, counting, and picking goods, by integrating deep learning algorithms into robotics. As a result, robots can identify packages (in less than 0.2 seconds) and transport them to the right place.

2). Use of AI to predict orders: A company (Lineage Logistics) in the food sector uses AI to predict orders. The specific algorithm was developed to predict the exact number of orders and the estimated time of arrival and departure of orders from its warehouse (ETAs, ETDs), so that workers can place the pallets in the correct order e.g., items leaving earlier are placed in front and items leaving later are placed further back. The use of AI to put the pallets directly in the right place and predict orders resulted in an increase in efficiency by 20%. For a company that handles an average10 of 15 million kilograms of food is this result spectacular.

3). Predict the ETAs using AI: Like the previous use case, another company (Infinera) adopted AI to predict the ETAs of packages, based on historical data (e.g., previous data deliveries) in combination with weather data, and customer feedback data. The implemented AI is based on machine learning that provides information about production/stock and delivery time to sales staff and customers to help reduce time and predict delivery.

As a result of the implementation of AI, the company can take decisions faster and improve customer satisfaction, as customers are instantly informed about the availability and time of arrival of the products.

4). Delivering goods with AI-based autonomous driving vehicles': A last-minute logistics company (Marble) uses AI-based robots to deliver different types of items, ranging from medicines, groceries, and packages, much faster and more efficiently than humans can. The company started first to deliver food through an app and has next expanded with the delivery of medicines, groceries, and packages.
The robots use LIDAR technology to navigate on sidewalks and avoid pedestrians. They can keep track of what the conditions are on the walkways so that the routes are always more efficient and cost-effective.

5). Use AI application in maintenance: There exist multiple practical examples of a successful application of AI in maintenance. One of them is the way Tesla orders the parts for the cars, based on AI technology that helps the company to predict when one part breaks or needs to be replaced. Tesla cars run self-tests and diagnoses to determine whether there is a need to replace a part and order it automatically. Tesla uses a combination of AI and IoT to measure the condition of the parts of the car.
Another example is the airline company Easyjet which makes the maintenance of its aircraft more efficient using AI, based on a digital aviation data platform, to predict aircraft maintenance. The data platform enables easyjet to collect 60 times more data than other systems. This provides valuable information to the engineers to detect and replace parts before they fail. As result, the company can prevent the number of occurrence of delays and flight suspensions arising from technical problems.

A final example of the practical use of AI is the AI application in farming (agriculture). Many companies are using AI in farming, especially the implementation of autonomous machines, to make farms more efficient and human life much easier. For example, a UK startup company has implemented robots into fields to map and identify weeds using cameras. The objective is to map and identify the millions of weeds in a field to eliminate them. Another Danish company, called Farm Droid, uses a solar-powered robot that can stay in the field for the whole growing cycle of a crop e.g., from the start of planting seeds in the field. During the planting of seeds, the robot drives up and down and remembers where every single seed is planted. The bot then goes back, and weeds around those seeds. The robot can do all this without using cameras because AI algorithms are trained to let the robot remembers where the seeds are. This technique allows the robot to weed around the plant without the need to use pesticides or herbicides.

AI in Mainports Logistics

5. AI in Mainports (port and airport) Logistics

Airports and seaports are the backbone of international trade and play a crucial role in connectivity development and global value chains. Ports and airports are also considered important multi-modal transport platforms and logistics nodes in international transportation systems. Historically, The Netherlands has been among the global pioneers in the development of maritime and aviation sectors. Both mainports (Port and airport) are highly competitive and considered the main economic engines of the Dutch economy.

To maintain their international competitive position, airports and ports around the world have been engaged in a race of digitalization and automation of their operational processes, including transport and logistics activities. Digitalization and automation have brought many advantages to the ports and airports, such as the development of new generations of ports and airports e.g., smart ports and smart airports, advanced use of digital data exchange technologies and systems, advanced automated processes, and the use of autonomous things (machines, devices, vehicles, etc.), and application of advanced robotics.

In The Netherlands, an increasing amount of money invested in the ports and airports has been used in accelerating the levels of automation and digitalization of processes and services, using the start of the art technological innovations in the AI sector. The main goal of the application of AI technology and systems is to realize a full integration of logistics supply chain activities with services and transport sectors, through the development of data-sharing platforms that can be used by communities of actors along the entire logistics networks. Data-driven chain cooperation, based on trust, security, and respect for data ownership, is crucial in adopting AI in port and airport activities. In an ecosystem formed by multiple autonomous actors with different goals and strategies, real-time digital access to relevant information and data can significantly improve the efficiency and effectiveness of logistics processes for all parties in the logistics supply chain. That's why most global seaports around the world have established the so-called "Port Collaborative Decision Making (PortCDM)" platforms, to support maritime operations as a part of efficient integrated transport operations between modes through coordination and data sharing (STM, 2018., p. 10). The same applies also to the case of smart airports, where digitalization and automation are integrated into advanced AI-driven systems and applied in airside activities as well as landside activities (see sub-section 5.2 below).

5.1. AI technology applications in ports and seaport logistics

The Dutch maritime sector offers to employ 385,000 workers and generates 45.6 billion of added value to the Dutch economy. The five main clusters of the Dutch maritime sector are the port of Rotterdam, the port of Moerdijk, the cluster of Amsterdam North Sea Canal area, Eemshaven-Delfzijl and Vlissingen and Terneuzen (North Seaport) (Source: Port of Rotterdam., 2019. Port vision).

Today, most global ports are confronted, at the strategic level, with the challenge of decarbonization and sustainability e.g., slow steaming (ETA, ETD), emissions (CO_2, air quality), energy and fuel consumption, etc. At the operational level, they are confronted with various challenges, ranging from lack of integration of port to inter- and multi-multimodal transportation networks, empty leg, and lack of efficiency and effectivity of port operations such as the use of equipment (train, ship, truck), and infrastructure (rail, road, waterways) and labor.

In this respect, AI technology and AI-based systems are considered by the maritime sector as a potential technology that can help the sector to solve, in a sophisticated way, different maritime and port logistics problems at sea level and port and terminal level. At sea level, AI technology can be applied in planning ports and routes as well as in the operative decision about vessel speed. At the terminal level, AI can be applied in the planning of the positioning and the (re)scheduling of a vessel at the berth, and in the planning intra-logistics and storage yard optimization e.g., the routing of trucks, straddle carriers, or automated guided vehicles, storage of containers and the repositioning of empty containers.

The adoption of AI in port and terminal activities and port process management can significantly improve the productivity of port activities and operations and increase the competitiveness of the ports. The use of AI-based optimization algorithms and machine learning models can improve the connection of ports and terminals to their hinterlands, reduce delivery time, eliminate unnecessary (manual) tasks, increase efficiency, and, lower costs (handling, transport, and logistics costs), and reducing idle time and waiting time (Dornemann, et al., 2020., p. 3338).

Most global ports around the world possess an information technology department that provides the users of port services with state-of-the-art tools, such as the terminal operating system (TOS) that provides the necessary information to assist users in their decision-making processes, such as an electronic data interchange, a web platform facilitating remote access to gate transactions and transactions of containers information, and a GPS based information of the inventory of containers in the yard.

It is expected that the adoption of AI will change radically the operation models of the maritime system that will encompass new capabilities such as voyage optimization and predictive maintenance, the coupling of shore-based centers within the decision-making, and operational control processes. The development of these new capabilities requires the setup of real-time data exchange platforms, based on the development of IoT, intelligent sensing and imaging technologies, Intelligent cameras, etc.

In port operations and planning, for example, AI is being leveraged in automated loading cranes at ports and for predictive maintenance of port equipment. In the future, AI is expected to help motor carriers gather and apply data for container deliveries more efficiently, and help to optimize cargo movement within ports given a variety of real-time, dynamic data inputs created and stored in central platforms or portals of information. In other words, AI can benefit ports by supporting the planning of port operations, and route optimization, enabling the prediction of arrival and wait times, improving green steaming, short turn-around times, just-in-time operations, and better utilization of fixed assets by predicting equipment failures and maintenance needs.

More specifically, there exist many areas and domains in the maritime sector and port activities where AI can be applied. In what follows, we present and discuss some key application areas where AI technology will revolutionize the way the ports will operate and develop in the future.

1). Smart shipping: Smart autonomous ships are seen as a potential field where the potential adoption of advanced AI technology will revolutionize maritime transport and port logistics, and possibly also the existing business models. Smart ships encompass a range of elements of operational efficiency and safety of the maritime transport system.

Currently, autonomous ships are still in the development phase and if developed, which could be the case in the future, they will not be able to function in a conventional port that lacks the corresponding port infrastructure, especially the port systems supporting the intelligent systems integrating AI technology, IoT and other intelligent transport systems.

Autonomous ships require the application of AI systems that can sense, recognize objects, and make decisions. However, the main challenges in the development of autonomous ships are the complexity and reliability of sensors and automation systems, and the safety and efficiency in the interaction between autonomous ships and the humans on shore (port authorities, towage, anchoring, berthing, mooring, cargo handling, etc.) and with other autonomous ships e.g., the interaction between Vessel Traffic Services (VTS)) and the automation systems. consequently, the most important milestone in the development of autonomous shipping is the development of an adequate and efficient remotely controlled engine room and the enhancement of navigational infrastructure, and the development of advanced systems that facilitate communication between vessels and ports, including traffic guidance systems, and port-service vessels (e.g., tugs and pilotage services).

Furthermore, a combined application of AI technology into an open simulation platform with the development of digital twinning of the port systems, are considered very promising innovative solutions for the development of smart shipping and smart ports. The development of the port and vessel digital twin system requires the transition from a vessel-centric perspective to a system-of-systems view of port-ship interactions and responses. In this perspective, the adoption of AI systems and AI decision support applications can help ports to real-time monitor the state of the waterway, the shipping movements, and the exact position of ships at sea, route, and terminal through Vessel Traffic Services (VTS).

According to SINTEF/TCOMS (2020), the main critical targets of the potential application of AI to accelerate the establishment of smart and autonomous shipping, are 1). Rules and regulations. 2). Automated information exchange. 3). Smart ships. 4). Autonomous ships. 5). Smart ports. 6). Ship physics. 7). Technical operations and maintenance. 8). Innovation eco-system.

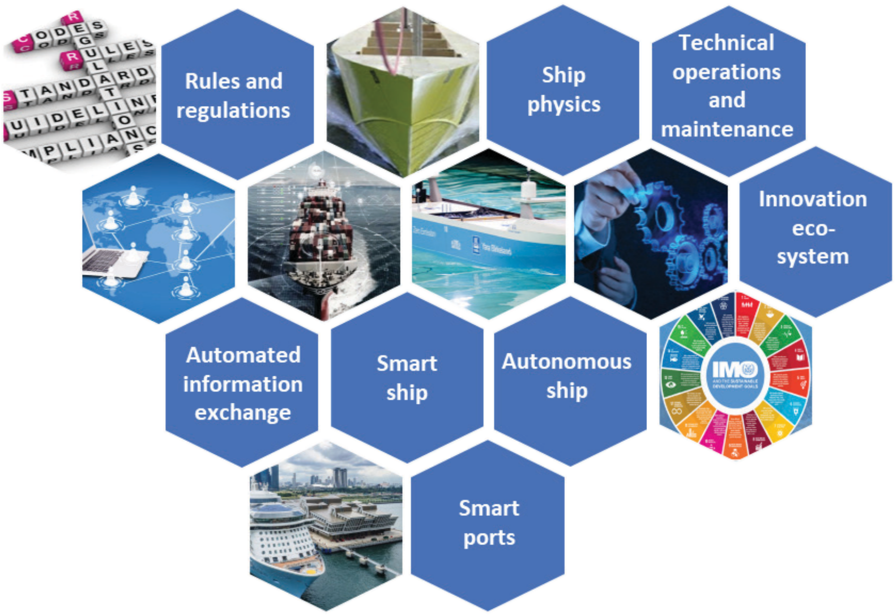

Figure 16. Critical targets of AI applications in smart ports and autonomous shipping.
Source: SINTEF/TCOMS (2020., p. 9).

Note that for functional operational and safety standards, the sail of autonomous ships requires real-time interaction with shore control centers (SCC) to allow remote pilotage to be performed for these ships. This is possible by enabling autonomous shipping to access high-bandwidth data communication powered by 5G connectivity networks.
In the case of the adoption of autonomous ships in short-sea shipping activities, the expectation is that short-sea ships will be increasingly equipped with partially autonomous functionality (autonomous navigation only during some parts of the voyage). Autonomous navigation in short sea shipping relies on international cooperation, and more specifically on the implementation of the new IMO legislation and regulation concerning the functional and technical standards of autonomous ships.
Finally, concerning inland shipping, it is believed that by 2030, highly automated sailing will be introduced in inland shipping transport. Automated inland vessels will use artificial intelligence and various sensors on board for large parts of the journey, supplemented with data from waterway authorities and data from other ships. The onboard system will be able to read the waterway and water level, warn the operators, anticipate changes, and resolve traffic situations involving other ships. Currently, most inland shipping vessels have intelligent warning systems on board, that support the crew in sailing smoothly and safely. Part of the inland shipping fleet can sail semi-autonomously, supported by the crew on board or from a shore control center. However, fully autonomous inland vessels (e.g., no crew on board and no crew in a shore control center) are not expected to be developed by 2030.

2). Smart port logistics: Ports serves as logistics platforms and as the interface nodes linking the sea to land. As mentioned before, with the advancements of technological innovations, many ports have deployed smart innovative solutions to optimize port operations and enhance the productivity of shipping activities. One of these solutions is the digitalization of the port operations and logistics activities by deploying advanced digital platforms, based on secure and reliable digital information and data exchange systems, to coordinate port-logistic operations of cargo across multimodal transport and logistics nodes. The next step is to integrate AI into existing digital platforms to build a complex system-of-systems digital platforms that can predict future operational scenarios, and anticipate potential incidents, bottlenecks, and disruptions. A continuous improvement of digitization and automation in port infrastructure, port logistics operations, and all ship-related operations are necessary for the ports to fully exploit the benefits of deploying artificial intelligence technology and the future smart autonomous ships.

The adoption of AI systems and models will enable the ports to directly tackle optimization challenges and help them to take the right decisions based on advanced ML/DL models, predictive modeling algorithms, and simulation techniques.

Also, the integration of artificial intelligence solutions with the use of LiDAR technology applications and digital twins' decision support tools, will help the ports to take full advantage of real-time visualization, simulation, and advanced analytics capabilities to improve port operations and planning.

Currently, advanced LiDAR technology solutions are used in ports and port terminals e.g., on cranes, vehicles, and stationary infrastructure, etc., to help solve multiple critical applications, including positioning, navigation, collision avoidance, bulk material profiling, and comprehensive safety monitoring of the port area and terminals. The real-time data collected by LiDAR sensors provide a detailed and highly accurate visualization of activities in the ports.
The adoption of advanced AI-driven solutions will benefit ports in many areas and activities of port operations and port logistics.

a). Operational planning systems: Digitalization of port operations and communications, planning, and execution control are critical factors to enhance port resiliency when facing challenges and disruptions of port operations. Current planning systems are robust against potential defects and disruptions. These systems use reliable data and information systems for the daily operations of port terminals, including data about ETAs and ETDs of ships and containers, loading and unloading locations and times, planning of workers/employees, times of arrival/departure, and location of trucks/vehicles, and where to pick up or deliver which cargo. Note that there exist multiple levels of systems where digitalized information and data are used in planning systems: First, the Terminal Operating System (TOS) provides all transactions of a terminal. Second, the single window-based systems, or Port Community Systems (PCSs), integrate the information systems of different stakeholders that are part of a port community. Third, digital systems of information and data exchange between different ports.
Many choices and decisions are made on daily basis by the port terminal managers and operators when managing resources and tasks that are necessary to carry out the cargo transfer processes within a terminal, and/or the coordination of cargo transport between the port and the hinterland. These decisions in planning, execution, and control are supported by Decision Support Systems (DSS).
The DSS is based on artificial intelligence algorithms and mathematical models to support the decision maker, usually implemented as modules of the TOS system. The use of ML algorithms helps port terminal authorities to predict the potential disruptions and delays in port operations, such as the dwell times of import of containers at a terminal, delay of ships, or delay of trucks/vehicles on road, etc. Based on these predictions, port terminal authorities can take appropriate decisions to prevent disruptions by applying better policies, for better equipment utilization at the port terminal.
The application of AI is of great help to port authorities in dealing with uncertainties and high peak demands on the landside port area. AI can be integrated with Truck Appointment Systems (TAS) or Vehicle Booking Systems (VBS) to mitigate congestion in the port. Such systems based on AI algorithms can help port terminals accurately determine the assignment of gate capacity to the different containers that are planned/expected to arrive. These AI algorithms can recommend slots assignment per service or segregation of containers may improve truck turnaround times and enhance yard equipment productivity due to improved capacity management for all resources at the terminal.

b). Self-learning algorithms: The deployment of AI technology and AI systems in the future smart ports, based on machine learning, can help ports to develop robust and self-learning predictive models that are capable to adapt to changes in the port environment. The full exploitation of existing edge cloud computing will enable AI-based machine learning algorithms to capture, update and analyze various data generated by different transportation modalities and port activities within the port. This will port authorities to better control and management of port and port infrastructure, enhance the planning of resources and personnel, simplify and accelerate documentation processing and improve the efficiency of logistics processes by providing real-time transparency to partners along the logistics supply chain on the status of their shipments.
Also, AI can be deployed to monitor assets and detect anomalies and potential failures of equipment in the port terminal. Indeed, machine learning algorithms based on sensor data can be trained to monitor variables, such as temperature, vibrations, etc., and feed data into centralized analytics software to spot anomalies in the data patterns that point to possible future equipment failure. Besides identifying potential failures and reducing downtime due to unscheduled and expensive equipment malfunctions, AI systems can also be used to optimize the performance of engines and reduce fuel costs.

c). Fully predictable port: The application of artificial intelligence and vision technology in modern ports and container terminal operations are considered critical components in optimizing and coordinating the handling of ships and enhancing port operations and logistics processes. With the thousands of moves and movements flow of containers, ships, vehicles, trucks, trains, etc., that happen every day in port terminals, the application of intelligent systems, such as AI decision support tools and planning algorithms, that assist and help the port authorities to take the right decisions and to maintain and/or increase the level of efficiency of port operations and logistics processes become crucial.

Riessen et al. (2016) studied the development of real-time decision rules for suitable allocations of containers to inland services. They applied an ML alongside optimization algorithms approach. The optimal solutions to problem instances were first generated by an exact-solving method. Then a decision tree was created using a supervised learning method, which learns decision rules for the allocation of a container to a suitable service based on the container and older properties, such as the time of availability, the transportation lead time, and container mass. This set of rules is then used in real time as a decision tool to provide a set of suitable services to a human planner. This study shows that the developed decision support system can reduce inefficiency, hence the transportation costs without extensive IT development.

Automation in ports and terminals on the landside is regarded as a viable option that can promote efficiency and sustainability. The use of Automated Guided Vehicles (AGVs) is regarded as an enabling technology of intelligent port logistics. The limited number of empirical studies investigating the use of AGVs in container port terminals focus on routing and scheduling aspects concerning performance improvements, such as the number of AGVs, the travel distance by vehicles, and/or efficiency and effectiveness of the applied analytic approaches (Fenton et al., 2018). The majority of modeling approaches apply exact solution methods who has a major limitation to tackle dynamic changes and be implemented in real-world problems that require immediate responses. Therefore, in the case of automated container port terminals, AI applications could support sensor-driven robotic operations in complex environments that entail real-time information gathering and processing for operational efficiency (Selke et al., 1991). The increase in the importance of AI in solving practical problems related to port terminal operations is indicated by the increase in the application of heuristic and metaheuristic searches, a core area of AI, during the last few years.

Having said that, AI is considered a key element in the development of a digital twin model/system of the port, by integrating the data platform (AIS data, sensors data, LiDAR, radars and cameras, CRM, assets management data, GIS data, etc.) with AI systems and AI algorithms for monitoring, decision making, and predictive analytics.

Note, however, that the scope of digital twins is focused on three different twins, which can serve different purposes and port activities operations areas: discrete digital twin, composite digital twin, and organizational digital twin. The discrete digital twin focuses mainly on port object monitoring, environmental conditions monitoring, individual object optimization, and historical analysis. The composite digital twin focuses on monitoring port object interaction, context management, process optimization, and real-time decision support, while the organizational digital twin focuses on monitoring organizational effectiveness and on strategic business value maximization.

More generally, the integration of AI with a digital twin, which mirrors all resources, operational processes, transport, and logistics activities within the port, tracking ships' movements, traffic flows, weather, geographic information, and water depth data, etc., will facilitate the transition towards the fully or near fully digital smart port and to accommodate the fully autonomous ships.

3). Smart manufacturing in the shipping industry: AI technology is of great importance in the production activities of the shipping industry and port operations.

In the shipping industry, AI technology is applied in ship design by applying genetic algorithms and other optimization techniques in the design of standard and autonomous ships. In the engineering of the shipping industry, AI technology enables the transition from modeling to decision-making and pattern recognition and classification of operational data obtained from LIDAR, sensors on board ships and onshore, terminals and platforms, etc.

Also, in project and production planning, the application of AI systems and algorithms helps to better interpret and translate Computer-Aided Design (CAD) data and data of the yard into one system where different specialist suppliers can collaborate. AI-based decision support systems help to improve dynamic planning and determine the scope of work and lead time per job, by providing real-time information from the 3D digital product model and the digital control information to digital machine tools.

Finally, the digitalization of the production environment using digital-twin and data-fusion technologies that combine sensor data and pattern recognition algorithms from physical production lines and digital product models for effective implementation of automatic and robotic production technology (welding, assembly, coating, etc.).

4). Smart asset management: the most important AI application in asset management is computer vision where data and classified information are retrieved from images or videos to estimate the condition of an asset or equipment. AI algorithms are trained to detect anomalies or deviations in an asset or equipment (e.g., machines, engines, devices, etc.), using supervised and non-supervised machine learning models. AI is also deployed in asset management by applying predictive modelings, such as mathematical optimization or simulation techniques, to support decision-making. These types of AI models help to predict the type and time of failure of assets, and based on that planning of the maintenance schedules can be made.

The application of AI to maintenance and asset management can provide significant benefits for the development and deployment of preventive maintenance scenarios since operations are highly dependent on equipment and machinery reliability. Consequently, real-time monitoring of critical assets and equipment for predicting potential failures or problems enables the staff to respond on time and avoid unplanned breakdowns.

More generally, AI-based predictive maintenance is a good strategy for port terminals in detecting and managing, in advance, assets and equipment incidences, hence improving the overall efficiency and performance, and the lifetime of the equipment.

5.1.1. Practical examples of AI applications use cases in the maritime sector and port industry.

There exist many examples in the world of developments of potential innovative solutions based on AI technology in the maritime sector and ports and logistics industries.

In what follow we present a number of these practical examples, where AI technology plays a key role in providing potential solutions that can be applied in the maritime sector, and ports and shipping industries (Ministry of Infrastructure and Water Management, 2021).

1). Communication networks technology: Concerning the development of new network technologies in the port industry, Nokia announced in 2021 that it will build a high-performance, industrial-grade LTE/5G private wireless network at the port of Seattle. The platform will offer reliable high-bandwidth, low-latency private networking, local edge computing capabilities, voice and video services, and a catalog of applications. Similarly, Europe's four largest mobile network operators Deutsche Telekom, Orange, Telefónica, and Vodafone are linking up to support the deployment of open Radio Access Network (RAN) technology across the continent. The implementation of this mobile network technology in Europe will not only benefit consumers and enterprise customers across Europe but also the maritime sector and ports and port logistics sectors as well. This is also the case of the zero-emission ultimate ship "Zeus" (the world's first hydrogen-powered ship) that is being developed using the latest advances in network technologies, such as 5G networks. It is expected that new business models and applications will emerge from the development of this new ship's technology. One example of such applications is the satellite-based image services provided by the Earth Observation Services Access (EMSA), which is considered Europe eyes in the sea. The EMSA offers services and information to the EU's surveillance and safety programs such as Clean Sea Net and Copernicus Maritime Surveillance.

2). Drones and autonomous boots and ocean robots: Among the emerging technologies, based on AI, is the use of drones in the port and logistics sectors. Drone technologies have the potential to transform traditional maritime operations such as inspection, safety and security, crime combat, shore-ship deliveries and remote inspections of ships and container cranes, and more.

Currently, there are multiple cases where the fully autonomous drone is tested in the field of inspection and control in the port and port terminal areas.

This is part of the port authorities' ambition to support the port's operational tasks related to safety and security using a network of autonomous drones. The objective of the practical cases is to test the various autonomous systems and operational networks of autonomous drones in a realistic and complex environment of the ports.

The port of Rotterdam, for example, is developing an unmanned traffic management (UTM) system that will manage and support the use of drones in the lower airspace of the port area. Drones will be integrated into ports' daily operations in inspection, surveillance, incident control, and combatting crime and drug smuggling in the port area. The port of Rotterdam is also envisaging the use of drones in the delivery of parts on board ships and/or taking cargo samples before the ship arrives at the port. A step further in the future of smart autonomous ports, drones are expected to play important role in freight and passenger transport in the ports.

A similar initiative was also taken by the port of Hamburg. The port has started using automated drones in inspecting and monitoring events happening in the port. Furthermore, drones can make maintenance and expansion of port infrastructure more efficient and can also be used to help the port authorities in situations where storm surges, accidents or other unforeseen disruptions may occur.

The port of Singapore has launched a Maritime Drone Estate (MDE) to support the development of drone applications in the port sector. The MDE provides a conducive space to test bed and develop drone technologies and operations for maritime applications e.g., shore-to-ship delivery, remote ship inspection, etc. The MDE is part of the port authority's strategy to invest in new port capabilities through the adoption of cutting-edge AI technology to build and strengthen the port innovation eco-system as a top international maritime center.

Besides the adoption of drones in the ports industry, global ports are also experimenting with the use and implementation of autonomous (sub) boots and ocean robots in the port area. One example of this kind of emerging technology is the "autonomous smart buoy" backed with a fleet of ocean robots, that will be tested within a closed platform by the Plymouth Marine Laboratory in the UK.

The experiments of this innovative solution use advanced sensors application and a high-speed above-water communication network, based on a 5G private marine network, that able vessels and equipment to communicate with each other.

3). Optimized remote data and visual support services: Nowadays, ports and the shipping industry (e.g., vessel operators) make use of data analytics to make the decisions that the analysis suggests on the state of operations, systems status, machinery health, and maintenance. In the shipping industry, for example, most data on speed, route, fuel consumption, and emissions are collected on board as ships have become more automated and standardized. With the application of data analytics and AI technology, the port and shipping sector can benefit from the integration of enhanced data and analytics with emerging AI technologies and systems.

An example of such use of data is satellite-optimized remote data and visual support provided to ships at sea by the software company AnsuR Technologies. The company's ASIGN system connects a pilot flying a UAV to remote viewers, bringing real-time high-definition UAV photos and video to decision-makers, in situations when the bandwidth of flying in locations is limited. Other use cases of this system include disaster and emergency management, security operations, and remote inspection of ports and maritime operations.

Another example is the use of the S-100 standard for universal navigational data, which represents the largest change in e-navigation since the International Maritime Organization's (IMO) Electronic Chart Display and Information System (CDIS) carriage requirements came into effect. This standard provides the framework to transform static information currently held in physical nautical publications into interoperable digital layers for use in ECDIS, to improve the mariner's situational awareness and enhance voyage planning and monitoring.

Also, a provider of space-based data services (Spire Global), provides global data sets to vessel operators that help them in improving the performance of voyages (ETAs) and optimizing vessels' engines (optimizing fuel and safety). The global weather data provided to vessels is collected from over 100 satellites, using machine learning techniques to enhance the data and provide global weather forecasts.

Finally, one of the biggest global shipping companies (Maersk) combines satellite data with dynamic AIS and AIS terrestrial data and customer data to optimize the vessel's voyage, by assisting tramp operators in keeping their vessels sailing at the optimal speed toward their destination. The application of AI-based systems to build a real-time picture of global maritime traffic enables the company to generate better recommendations on vessel routes and speed, in turn unlocking emissions reductions and revenue optimizations.

5.2. AI applications in Airport management operations and airport logistics

From a historical point of view, the aviation industry in general, and the airport sector, in particular, can be considered pioneers in the development and adoption of new technologies and technological innovations.

Compared to the logistics sector, where, according to Accenture (2022), 36% of large-, mid-, and small-size organizations have successfully adopted AI in their logistics and supply chain processes, global airports around the world have spent $ 4.1 billion on IT systems in 2020, against 5.1 $ billion in 2021 (ACI, 2022). The spending on IT systems increased from $ 7 billion in 2016 to $10 billion in 2018 before decreasing in 2019. This decrease is explained by the coronavirus pandemic that cut the airports' IT spending by more than half but also accelerated the need for more investments.

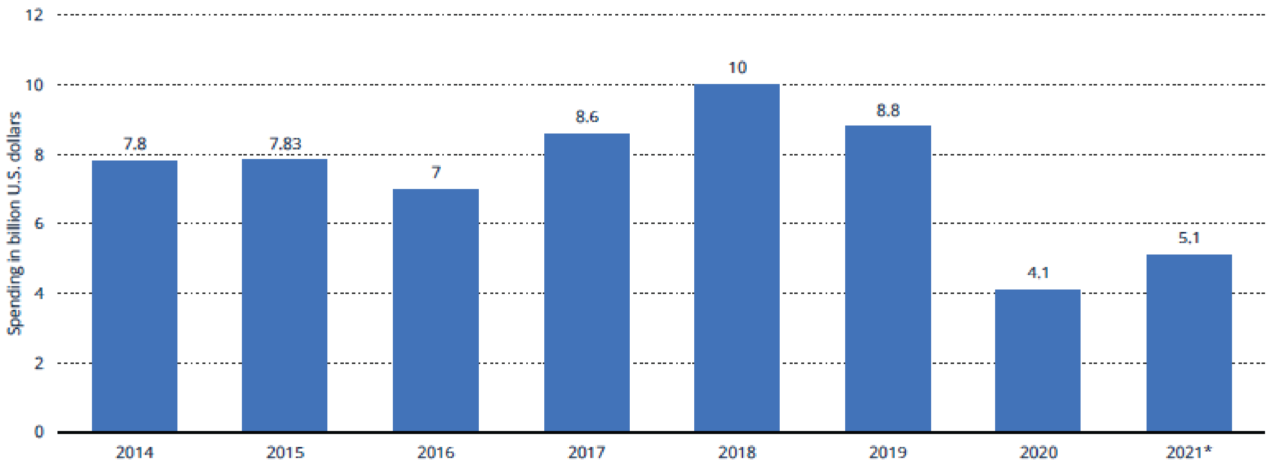

Figure 17. Total spendings in IT systems, by airports worldwide from 2014 to 2021 (in billion U.S. dollars). Note(s): 2014 to 2021; Planned value figures prior to 2018 were taken from previous editions of the report. Source(s): ACI; Savanta; SITA (2022).

A large part of airport investments and spending in new technologies and systems were oriented towards automation and digitalization of airport operations processes, more specifically consumer services, unassisted bag drop-in systems, security, and automated check-in services. Compared to 2015, 52% of global airports have implemented unassisted bag drop-in 2021, and 40% of airports implemented self-boarding and 35% of automated border control. Furthermore, 25% of airports in the world were planning to offer flight status notifications on mobile devices in 2021, such as flight status, CRM notifications, navigation/wayfinding, retail promotion, etc. This percentage share was as high as 60% in 2018 and 2019.

Investment and spending in the adoption of AI technology and systems have also increased during the last decennia. For example, the share of AI-driven chatbot services was less than 10% in 2017 and has increased since then to almost 15% in 2019 and more than 45% in 2021 (ACI, Savanta, SITA, 2022).

According to the ACI survey (2022), investment priorities of global airports by the year 2024 will be focused on cybersecurity (94%), cloud services (86%), self-service processes (84%), IT services (83%), and IoT initiatives (83%).

The share of future investments in new AI technology and AI systems between 2021-2024 is expected to reach 65%. Share of future investments is expected to be 81% in Business Intelligence (BI),

74% in biometric ID management, 72% in data exchange technology, 71% in 5G communication network, and 63% in a digital tag.

More generally, the aviation industry and the airports are taking a keen interest in emerging technologies, more specifically the potential adoption of AI technology such as machine learning and deep learning, to increase the levels of automation, cyber-secure data sharing, and connectivity in air traffic management (ATM) as well as the application of AI-driven intelligent systems in maintenance, engineering and prognostics tools. AI technology and AI applications are also used to streamline business processes, air transport logistics, and customer service provision. The figure below shows the share of airports globally that have implemented or planned to implement AI technology and applications in airport operations and processes by 2022.

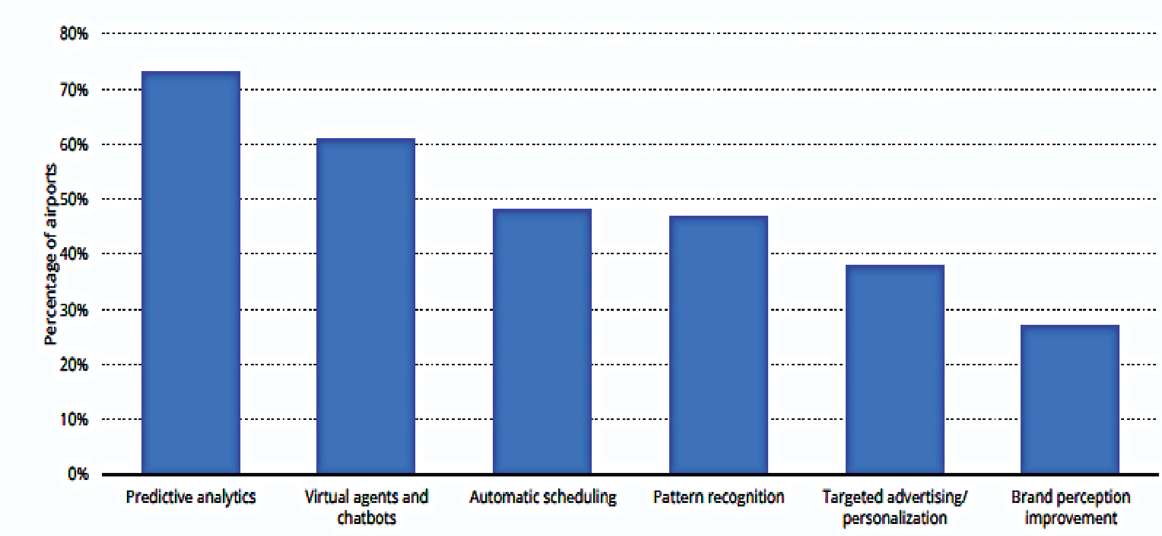

Figure 18. Percentage of airports with AI use cases implemented or planned by 2022, by type.

Source(s): ACI; Savanta; SITA (2022).

The figures show that about 72% of airports have implemented or planning to adopt predictive analytics tools and models/algorithms, followed by the implementation of virtual agents and chatbots (60%), automatic scheduling (49%), pattern recognition (46%), targeted advertising/ personalization (39%), and brand perception improvement (about 29%).

In opposition to the airports, the airlines are expecting to invest mainly in AI technology (82%), followed by business intelligence (78%), data exchange technology (70%), RFID (62%), near field communication (43%) and blockchain (42%).

The adoption of AI technology in aviation holds great promises for enabling the sector to improve airport operations, air traffic services, optimization of air traffic management (ATM) network services, efficient management of airport infrastructure and landside transport networks, as well as to build resilience to disruptions and cope with changes in air demand and increasing complex air traffic and infrastructure capacity.

Air traffic management (ATM) is an ideal candidate for advanced automation and augmentation through AI because AI is acknowledged to manage the flight journey more effectively (e.g., flight route optimization), and help with intelligent maintenance of airline engines and other machines, improving airline safety, and the optimization of Air Traffic Control (ATC) systems, and airport decision making through the improvement of Airport Cooperative Decision Making (A-CDM), etc. The Airport CDM is an advanced airport information system, which focuses on aircraft turn-out and pre-departure processes, that aims to improve the efficiency and resilience of airport operations by optimizing the use of resources and improving the predictability of air traffic.

Note that, digitalization and automated systems are already playing a big role within the aviation industry. Airlines, for example, use artificial intelligence (AI) in many areas, from network prediction and performance to planning new routes to communicating with customers, optimizing fuel efficiency, and even conducting predictive aircraft maintenance. The repetitive procedures of existing airlines and aviation IT systems generate huge amounts of data, that can be used by AI systems to improve the efficiency of airline and airport operations in many ways and allow human operators to focus on safety-critical tasks.

In this respect, machine learning algorithms are applied in aviation to enhance the monitoring system of the gas turbine during flights, increase safety when an airplane is landing, or check the engine on-board using the Probabilistic Neural Network (PNN) or automated Supervised Random Forest (SRF) algorithms to accurately detect turbulences. Furthermore, the application of AI systems in aviation helps pilots to avoid deviating from the pre-determined route and minimize fuel costs, while enhancing air control management.

Also, airlines use automated marketplaces that help them to define flight allocations, without revealing commercially sensitive pricing data, and build seamless multimodal travel information systems that help improve passenger journeys.

Perhaps, the most important application fields of AI technology and systems in the aviation sector and airport industry are network prediction and performance, which is very sensitive to weather conditions and high uncertainty of Air Traffic Flow Management (ATFCM) operations. The application of AI in improving network operations help airports to optimize air traffic flows and airport operations in terms of improving capacity and demand at the local and network level. This is done by applying machine learning models to predict demand or detect conflicts and resolution and delay propagation.

Future applications of AI technology can help the aviation sector and airports to develop a smart airport of the future based on the integration of airport operations with advanced and seamless multi-modal transportation systems from door-to-door passenger travel journeys. The optimization and alignment of the multi- and intermodal transportation system with airports are therefore of utmost importance for the overall performance of the (future) of the aviation sector and air transport system, especially regarding the integration of transport modes at regional, national, and European levels.

Working towards this goal, various initiatives took place in Europe to stimulate the development of AI technology in the aviation and air transport sector and increase the integration of air transport into existing transport systems.

5.2.1. Practical examples of AI applications use cases in the aviation sector and airport industry

Below, we present the most important innovative initiatives at the European level that might serve as a practical example of research and initiative aiming at the implementation of AI technology and systems into the aviation sector, and airport operations in Europe (SESAR-JU, 2022).

(1). The first examples concern projects focusing on the development and implementation of AI-based systems in air traffic management.

The first example concerns the development of an AI-based blockchain platform to improve the operations of ATM (AICHAIN). The project aims to develop the so-called Federated Machine Learning (FML) that can guarantee the cybersecurity and privacy of data gathered and shared by airlines. The FML platform applies predictive AI to better predict and plan flight allocations by air navigation service providers. The main objective of this project is to modernize Europe's ATM system and to cut costs (and delays) at airports, using machine learning to sensitive (and non-sensitive) data in a decentralized, protected way.

The second example concerns the development of transparent AI and automation to air traffic management systems (ARTIMATION). The main objective of this project is to investigate the application of AI methods in predicting air transportation traffic and optimizing traffic flows, using eXplainable Artificial Intelligence (XAI) algorithms, to address the challenge related to the transparency of automated systems in the ATM domain. This project has developed algorithms using XAI techniques to support two common operational tasks: air traffic conflict resolution (such as rerouting aircraft to avoid collisions) and delay propagation (e.g., understanding the reasons for delayed flights). A proof of concept of transparent AI models was developed that can be adopted for a range of tasks, as well as adaptable over time, offering safe and reliable decision support.

The third example concerns the development of highly automated air traffic controller workstations with AI Integration (HAAWAII). This project focuses on developing advanced automatic speech recognition software based on deep neural networks for safer air traffic control, focusing on the communication between the pilots and the controllers. Tests of the developed prototype show that combining voice with radar data improve significantly the semantic level of ATM system e.g., 97% recognition rate for aircraft call signs used by controllers. Machine learning was also applied to create a Readback Error Detection Assistant (REDA). Laboratory tests of REDA show promising results e.g., a success rate of 80% from offline evaluations of transcriptions from real-life data and a false alarm rate below 20%.

The fourth example concerns the development of modern ATM via human-automation learning optimization (MAHALO). This project aims to better understand the type of automation best suited for ATC systems, by looking at how much AI should be used, where it would be most beneficial, and whether it should perform tasks autonomously or serve as a tool to support the human controller's decision-making. To answer such questions, a hybrid machine learning system was developed and trained to solve critical ATC tasks, such as detecting and resolving en-route traffic conflicts. It is expected that results will help to reduce delays, improve efficiency and increase the safety of air traffic control.

The fifth example focuses on the development of predictive AI into air traffic management workflows for better decision support (SafeOPS). The main objective of this project is to strengthen safe and scalable ATM services through automated risk analytics. In this project, predictive machine learning is integrated into existing human-driven ATM systems to make ATM processes more efficient and safer, especially in predicting go-around events ahead of time.
A similar project called TAPAS (Towards an Automated and exPlainable ATM System) was initiated to develop new AI-based techniques that provide transparency for automated flight management systems. in this project, an eXplainable AI (XAI) framework and techniques were developed and integrated into real-time simulations to explain decisions made by the system. The framework was tested in a practical real-world situation in Spain (by ENAIRE).

The final example of AI application in air traffic management concerns the development of powerful AI-based simulation models, using machine learning methods in combination with simulation models and big data analytics for ATM performance analysis, to model Europe's crowded skies (SIMBAD). The main objective of this project is to develop state-of-the-art modeling techniques (e.g., modeling air traffic at different spatial and temporal scales) based on artificial intelligence, and using new machine learning approaches, to improve current air traffic microsimulations by integrating new technologies into ATM systems (pp. 25-26).

2). The second example concerns projects focusing on the development and implementation of AI-based systems in <u>air traffic management and safety improvements</u>.
The first example here concerns the development of an automated situational awareness system (AISA). One of the major problems in aviation is the very high workload capacity of air traffic controllers, especially during busy periods. The high workload cause aviation capacity problems both on the ground (delayed flights) and in the air (congested air space). One solution to this problem is the application of automation and AI systems. The implementation of AI can help to handle workload (e.g., specific tasks), and to free up the mental capacity of controllers so they can handle more aircraft and focus on safety-critical tasks. The application of AI is focused on monitoring and performing artificial situational awareness tasks of air traffic controllers, such as detecting conflicts (e.g., safety in approach and landing of aircraft).

The second example concerns the development of AI-based multi-hazard monitoring and early warning system (ALARM). This project focuses on the development of an AI-based system that can help aircraft to avoid dangers and disruptions while flying, by offering real-time monitoring service and precise information on natural events such as thunderstorms and volcanic ash clouds. The developed AI system is based on gathering and processing near real-time data from ground-based and satellite systems. The ML models are used to identify the displacement of particles and gases derived from natural hazards, as well as extreme weather situations. The next step is the development of predictive models that provide accurate forecasts between one hour ahead and a day ahead.

The third example concerns a project called "SINAPSE" which focuses on the software-defined networking architecture augmented with AI to improve aeronautical communications performance, security, and efficiency. In this project, new AI software architecture is developed (Software-Defined Networking (SDN)) to defend them against cyberattacks and help manage the aeronautical systems more efficiently by preventing disruptions in the air communications networks. The deployed AI system automatically checks for faults in the networks and algorithms, based on machine learning, analyze the network traffic for signatures known to match cyberattacks. (pp. 27-28).
Finally, a project was initiated to develop a semi-automated flight allocation swap platform for airlines (SlotMachine). The main focus of this project is on the development and implementation of AI-powered flight slot allocation that helps airlines to cut costs and delays, using blockchain technology. The project investigated the potential of a lightweight distributed ledger that securely links records together using cryptography. This enables several users to make calculations using combined data, without revealing their input.

3). The third example concerns projects focusing on the development and implementation of AI-based systems in the integration of air transport operations into multimodal transport systems for efficient passenger flow management.

The first example in this type of project concerns the development of integrated multimodal airport operations for efficient passenger flow management (IMHOTEP). This project aims to put passengers at the center of multimodal mobility, as airports evolve into multimodal transport hubs. AI can help to better map the passenger journey, laying the groundwork for a seamless and sustainable experience. The project has developed interconnected platforms and services that enable real-time collaboration between airports and ground transportation to efficiently manage the passenger flows in and around the airport and airport terminals. The data used in this project was collected from personal mobile devices and digital sensors. The gathered data is then fed into a set of algorithms capable of reconstructing passenger flows in real-time and for different stages of the passenger journey. The outcomes of this process are delivered in the form of so-called "Activity-Travel-Diaries" that were used for calibrating predictive models for forecasting the short-term evolution of airport and ground transport performance.

A very similar project to the IMHOTEP project is the extended ATM for the door-to-door travel (X-Team D2D) project. The X-Team D2D project aims to define, develop and initially validate a concept of operations (ConOps) for the seamless integration of ATM and air transport into an overall intermodal network, including other available transportation means (surface, water), to enable the door-to-door connectivity, in up to 4 hours, between any location in Europe.

Another project concerns travel information management for seamless intermodal transport (TRANSIT), which focuses on the integration of ATM with ground transport networks, using AI techniques to help seamlessly connect all the steps in a passenger's journey. This project develops a methodological framework and a set of software tools to support the design, implementation, and evaluation of new intermodal concepts and solutions.

The third project concerns synergies between transport modes and air transportation (Syn Air) and focuses on data sharing for a seamless D2D journey and improvement of planning and operations activities.

The latest project concerns the modeling and assessment of the role of air transport in an integrated, intermodal transport system (MODUS). The main objective of this project is the analysis of how air transport management (ATM) and air transport can better contribute to improving passengers' multimodal journeys and how this translates into an enhanced performance of the overall transport system. More specifically, the project focuses on the performance of the overall transport system by considering the entire door-to-door journey holistically and assessing the role of air transport within an integrated, intermodal approach.

4). The fourth example presented below concerns projects focusing on the development and implementation of AI-based systems in the improvement of network operations management.

The first example focuses on the development of AI solutions for weather prediction for network operations planning (ISOBAR). The performance and prediction of the air traffic flow network are very sensitive to weather conditions and the uncertainty in its prediction. This project aims to apply AI-based network operations that can address these challenges by including weather prediction, ATM and weather data integration, and demand and capacity (DC) imbalance characterization. For this, AI-based predictive models and other advanced technologies have been used to help air traffic managers to better anticipate (e.g., precisely and accurately predict) weather disruptions (for example thunderstorms and big storms activity) that can help to reduce delays and cancellations. The predictive models help also to predict the demand and capacity, by looking at scheduled flights, routes, weather, etc.

Another project concerns the development of network management services (DNMS), and more specifically on improving network traffic prediction. The focus of this project is structured around three main AI-based solutions: a). The dynamic airspace configurations (DAC). b). Enhanced network traffic prediction and shared complexity representation. c). A prediction algorithm to anticipate the performance degradation within the network.

Finally, the so-called "AEON" project (Advanced Engine Off Navigation) applies AI techniques to support the operations focusing on engine-off taxiing techniques. The project defined how to determine, in real-time, efficient and conflict-free routing plans for autonomous and non-autonomous aircraft taxiing from gates to the corresponding runways and the other way around.

AI and Ethics, Governance and Regulation

6. AI and Ethics, Governance and Regulation

Although AI technology is seen as a game changer in many areas that have been presented in this report, there are multiple pronounced reasons to put forward in explaining why AI adoption is holding back in specific areas and domains. Perhaps the most justifiable reason is the concerns related to interpretability and explainability, more specifically the risks of AI bias linked to algorithms and the transfer of key tasks and human decision-making power to autonomous AI systems. This fear of AI technology is often motivated by irrational motives because people who do not understand AI are more worried about its unintentional consequences e.g., concerns about privacy, data sovereignty, fear of losing power, an increase in inequality, the complexity of technology and fair to control it, etc. on the other hand, these worries and warning against the fetichism of AI must be taken seriously as a warning to not buy into the hype surrounding the new of AI technology, and the perhaps the unrealistic expectations and possibilities of what it can and cannot do. The implications of AI adoption on human life and the public domain are not quite clear as the technology is still in its infantile development phase. That's why AI ethics is currently one of the major topics discussed in the literature about the development, use, and application of AI in social, cultural, political, and economic domains. AI ethics can be defined as a set of guidelines developed to advise on the design and outcomes of artificial intelligence. The main goal of these guidelines is to minimize the risk of "artificial cognitive" bias in the design and outcomes of AI systems and applications (algorithms).

It is known that humans can have different sorts of cognitive biases that influence their behavior. Since the data used in all machine learning algorithms are based on human behavior, it's important then to structure experiments and algorithms with this in mind as artificial intelligence has the potential to amplify and scale these human biases at an increasing rate.

Note that AI bias occurs when an algorithm produces results that are prejudiced due to erroneous assumptions in the machine learning process. For example, some leading high-tech companies, like Amazon, Meta, and Google, etc., that focus on automation and data-driven decision-making to improve business outcomes have experienced unexpected consequences in some of their AI applications, due to algorithms design that lacks ethical standards, and the use of biased datasets extracted from user's behavior.

So, the risk of AI bias is mainly caused by the designers who develop/write the algorithms, choose data, and decide how to apply the results of the algorithms. Without collaboration between diverse teams of designers and developers of algorithms and AI systems (data scientist, business leader, programmer, etc.), in addition, to checks and balances, and rigorous controls and tests, unconscious bias and mistakes can enter, and then propagate and perpetuate when using the AI systems or applications.

Varga-Szemes et al. (2018) highlighted that machine learning algorithms should be created by machine learning specialists with relevant knowledge and an understanding of possible outcomes and consequences. Mitchell (2019) states that AI systems do not yet have the essence of human intelligence and that makes them vulnerable to kop with some human and ethical issues. For example, AI systems are not able to understand the situations humans experience and derive the right meaning from them. This barrier of meaning makes current AI systems to malicious people and hacker attacks (e.g., a hacker can make specific and subtle changes to sound, image, or text files, which will not have a human cognitive impact but could cause a program to make potentially catastrophic errors).

At the technical level, AI bias could happen because companies put big data through an AI data-driven model, partly or fully constructed by algorithms, and then blindly trust the output. This is known as the "Garbage in, garbage out" kind of AI model application. As AI applications do not understand the input they process and the output they produce, they are susceptible to unexpected errors and undetectable attacks. These can happen in multiple sub-fields of AI such as computer vision, medical image processing, speech recognition, and language processing. Also, AI bias can take place at the stage of setting up the AI model e.g., what the model should achieve, the stage of collecting data (that might reflect prejudices or is not representative of reality), and at the stage of preparing the data and selecting which attributes the algorithm should consider or ignore (Hao, 2019). Mitigating then the potential occurrence of these biases presents significant challenges for governments and organizations as the use of AI becomes more accepted and applicable in various domains (Dwivedi et al., p. 5).

6.1. AI challenges in social, economic, organisational, technological and political and legal levels.

Various challenges concerning the adoption of AI technology and its application at a social, economic, organizational, and technological level have been discussed in the literature.

1). At the social level, various challenges of the impacts of the adoption of AI technology on existing culture and cultural norms in societies. The implementation of AI technology in certain domains, such as healthcare, education, labor market, security, etc., can act as a potential barrier against certain groups of the population (Khanna et al., 2013). Some people believe that the implementation of AI would increase inequalities and divergence between individuals based on race, education, etc., and between social classes and groups of the population. This would apply not only to individuals and groups of people within the same nation but also at the global level between nations and human races.

2). At the economic level, the mass adoption of AI technologies will have an enormous impact on organizations and institutions in all economic sectors, not only in terms of investments, distribution of wealth, economic gains and losses but also in terms of radical change to working practices and internal organization of the companies. Also, AI technology could widen the gap between emerging and developed markets as well as the rich and poor (Bughin et al., 2018).

More generally, the effects of AI on future jobs and work are not only pessimistic, as a lot of people think that AI will result in job loss. However, this is something that usually occurs with every disruptive new technology that led to changes in the market demand for specific jobs and the shift of labor force/employment between sectors and activities. The positive side of the coin is that the adoption of AI can increase the share of jobs that require creativity and empathy, and hence a potential increase in the levels of technological innovations and growth of the creative sector.

3). At the level of data and data analytics, the implications of the integration of big data with AI have been widely discussed in the literature in the context of data sharing, data analytics, and data protection and security. For example, in 2016, GDPR legislation was created to protect the personal data of people in the European Union and European Economic Area, giving individuals more control of their data. In the United States, multiple individual states are developing policies that require businesses to inform consumers about the collection of their data. These policies have forced companies to rethink their data use and data management e.g., how they store and use personally identifiable data (PII). As a result, investments in data management and security of data have become a priority for businesses as they seek to eliminate any vulnerabilities and opportunities for privacy, surveillance, hacking, and cyberattacks. Also, challenges surrounding transparency and reproducibility were highlighted in many studies, especially in the context of acceptability relating to public perception. For example, Xu et al. (2019) study identified serious data challenges of using AI in cancer genomics. Their study shows that validating the benefits of AI solutions can be challenging in obtaining statistically significant patient outcome data.

4). At the organizational and managerial level, AI presents several challenges that have strategic implications for companies. The most important challenges are related to investments and costs of implementation, and the potential implications of AI on the internal organizational operations and tasks within the company and between the businesses in the same sector and across sectors. As Tizhoosh and Pantanowitz (2018) have shown in their study, the success of AI adoption in businesses depends on ease of use, financial return on investment, and trust.

Furthermore, besides the question of the interaction between humans and AI, the understandability and interpretability of AI outcomes could pose a challenge to the strategic decision-making of companies. In this context, it is important to understand first the importance of human vs computer interaction, and the urgent needs of the business before designing and implementing AI technologies to address them.

5). At the technological and technology implementation level, the most important challenge at the technological level exists around the architecture of IA systems and the need for sophisticated structures to understand human cognitive flexibility, learning speed, and even moral qualities (Baldassarre, Santucci, Cartoni, & Caligiore, 2017; Edwards, 2018).

According to some thinkers, AI technology will remain a "black box" even if the computer intelligence will be able to read unstructured data flow and resolve the algorithm opacity issue. This is because computer intelligence is built on unalterable lines of program code and internal un-editable sectors of its operating system. The technological challenges of algorithm opacity and lack of ability to read unstructured data were studied by Sun and Medaglia (2019).

The internalization of the ethical framework into AI technology can solve this issue, for example by mimicking humans in applying cautious language or descriptive terminology, not just binary language, and providing more transparency on the inside of the "black box" and how AI technology works.

6). At the political and legal levels, the main legal challenges posed by AI technology are related to legal challenges (i.e., AI responsibility) when serious errors occur (Gupta and Kumari, 2017), and the increasing complexity in adopting AI in the public sector. In this respect, the current legal framework needs significant changes to effectively deal with the challenges posed by the adoption of AI in government and public institutions. Wirtz et al. (2019), studied the challenges of implementing AI within government, and proposed a framework based on the concept of AI law and regulations that can help to improve governance, responsibility, and accountability of AI, as well as privacy/safety, while Sun and Medaglia (2019) have analyzed the challenges of applying AI within the public sector in China, with special focus on the impact of AI on citizens in the context of political, legal and policy challenges as well as external threats on national security from foreign-entities.

More globally, there exist various challenges related to the potential impacts of AI adoption at different levels. Most of these challenges can be resolved by devoting efforts to the development of new legal and juridical frameworks and the establishment of global standards and principles for AI ethics. Below we discuss and clarify this point further.

6.2. The need to establish standards principles for AI ethics

First, let's start with the rather optimistic idea that considers AI as a promising technology that can help to create a better and more equitable world. This idea could be exaggerated because it ignores the potential bias and risks of AI application on the life of individuals, groups of people, and society. By this we mean, the risk that AI can make decisions that are systematically unfair and unethical to certain individuals or groups of people.

Indeed, the rapid pace of change and development of AI technologies increases concerns that ethical issues are not dealt with formally when developing and implementing AI technology. Individuals and organizations can exhibit a lack of trust and concerns relating to the ethical dimensions of AI systems and the manner they use data. AI-based systems may exhibit levels of discrimination even though the decisions made do not involve humans in the loop, highlighting the criticality of AI algorithm transparency (Bostrom & Yudkowsky, 2011). For example, in using facial recognition, certain people of color can be misidentified more often than others (white people), which rises serious concerns and problems when this AI technology is used by law enforcement and police departments. There exist several cases of this that have been registered in the USA and Europe.

Another example is the application of AI in autonomous self-driving vehicles. A study conducted by Georgia Tech on self-driving cars found that self-driving cars guided by AI performed worse at detecting people with dark skin, which could put the lives of dark-skinned pedestrians at risk (PWC, 2022). A similar study conducted by UC Berkeley on the application of AI in financial services shows that several mortgage algorithms have systematically charged higher interest rates to black and Latino borrowers than the white color borrowers. In the same vein, researchers from Stanford University have found that automated speech recognition systems demonstrate large racial disparities. Other examples have shown that Natural language processing (NLP), the branch of AI that helps computers understand and interpret human language, can have racial, gender, and disability bias.

Although the AI sector has recently taken concrete actions to solve these AI biases, it is not clear how ethical and legal concerns, especially around responsibility and decisions made by AI, can be solved.

So, there is an urgent need for the development of responsible AI that is ethical (e.g., address the issue of fairness), robust (e.g., develop and report on controls related to AI models and processes), secure, well-governed (e.g., improve governance of AI systems and processes) and complaint (e.g., with applicable regulations) and explainable (e.g., interpretable and easily explainable).
According to McKinsey (2021), efforts to address ethical concerns associated with the use of AI technology in the industry are limited. According to the conducted survey, about 29% to 41% of respondents recognize the risks related to the ethical issue of adopting AI, and only 19% to 27% take practical steps to mitigate those risks.
The solution to this is to develop and enforcement of new regulations, ethical guidance, legal framework, adequate policies, and standards to prevent AI bias and the misuse of AI (Duan et al., 2019).

Recently, several ethical guidance frameworks based on rules and protocols were developed in collaboration between the government, researchers, and companies to construct and implement AI in society. The main principles considered in the development of these guidelines concern respect for the privacy and autonomy of individuals, the application of an AI ethical code of conduct (e.g., non-bias algorithms around race, sex, political orientation, etcetera), and justice (e.g., fairness and equality). In Europe for example, the EU guidelines on Trustworthy AI (TAI) were developed in 2019 to ensure the protection of people's fundamental rights while still allowing responsible competitiveness of businesses.
In April 2021, the EU developed the "AI Act" proposal for regulating the placement on the market and use in the EU of AI systems. The Act was passed through the EU legislative process and is expected to be voted into law in 2023.
The proposal introduces the obligation to provide minimum information by all AI systems in use, in addition to other requirements such as risk assessments and quality management, especially for AI systems that pose higher risks to users. Furthermore, the proposed AI Act prohibits the use of certain types of AI-based techniques like social scoring, real-time biometric remote identification, etc.

In the USA, the Government Accountability Office (GAO) released an accountability framework report for federal agencies and other entities to help managers ensure accountability and responsible use of artificial intelligence (AI) in government programs and processes. The main objective was to identify key practices to help ensure accountability practices and responsible AI use by federal agencies and other entities involved in the design, development, deployment, and continuous monitoring of AI systems. The accountability practices focus on the principles of governance, data, performance, and monitoring.
The figure below gives a summary of the GOA's AI accountability framework.

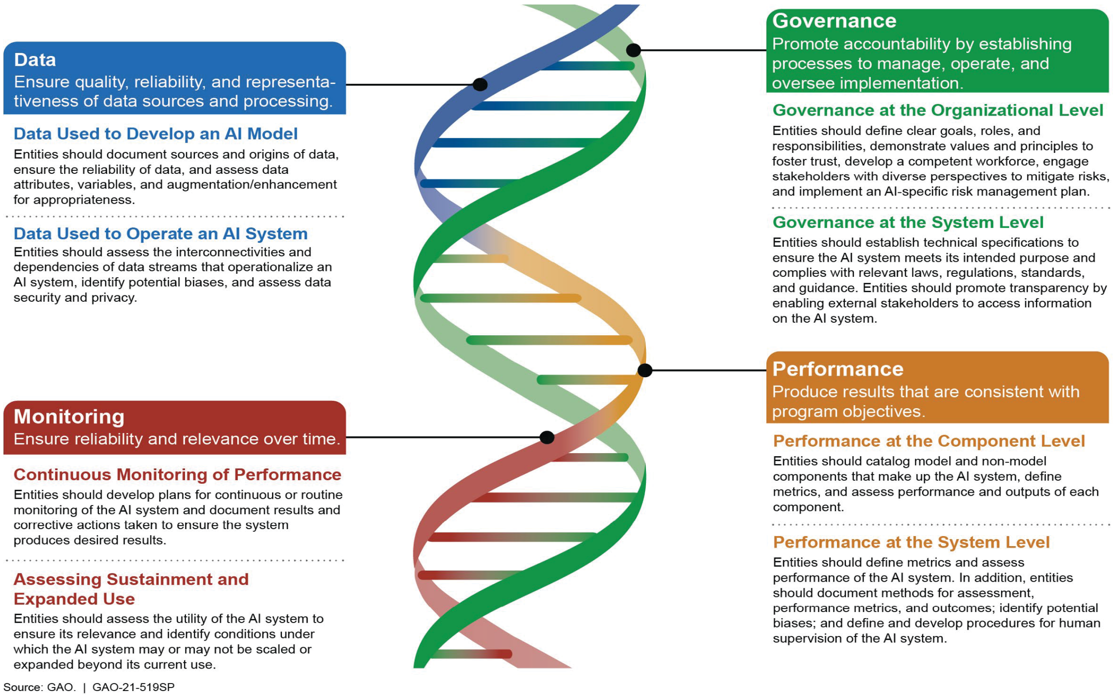

Figure 19. GOA's AI accountability framework. Source GOA (2021).

The main principles of the GOA's AI accountability framework are:

1). The principle of governance, which fosters trust, mitigates risks and establishes governance structure and processes based on clear goals (i.e., ensure that intended outcomes of AI systems are achieved), roles and responsibilities (i.e., ensure effective operations and timely corrections), and values (i.e., ensure public trust in the responsible use of AI systems) to all entities involved in the design and implementation of AI systems. It ensures that every developed AI system must meet its intended purpose and respects laws, regulations, standards, and guidance in developing and deploying AI technology and systems.

At the organizational level, the establishment of the principle of governance helps businesses to promote transparency, accountability, and responsible use of AI systems by integrating ethical AI in their internal governance and regulatory and legal departments. Also, the development, deployment, and monitoring of AI systems are very important for the development of a multidisciplinary workforce and the implementation of the AI-specific risk management plan related to direct investments.

2). The principles of data and performance, which focus on the quality of the data, reliability, representativity, and accessibility of the data, as well as documentation of sources and origins of data, description of the methodology, attributes, variables, etc., and the performance of the AI systems.

The main purpose of the data principle is to avoid potential bias and risks based on the used data in AI systems (e.g., inequities, social concerns, security, privacy, etc.). Best practices that must be implemented in this respect are good documentation of model components, along with the operating specification and parameters, the use of precise, consistent, and reproducible key metrics, and assessment of the performance of each component for the operational context of the AI system. In addition, the documentation of the methods for assessment, performance metrics, and outcomes of the AI system increases the trust and transparency of the AI system over its performance.

3). The principle of monitoring, which is closely related to the development of plans for continuous monitoring of the results of the AI system. The documentation of the results and eventual corrective actions that have been taken to promote traceability and transparency of the system are important elements of the monitoring principle. In addition, assessment of the utility and performance of the AI system, in terms of relevancy and applicability (e.g., the issue of scaling up the AI system to other cases, activities, sectors, etc.), must also be part of the monitoring principle.

6.3. Ethical AI and regulation in transportation and logistics

The challenges associated with adopting AI and automation in transportation and logistics sectors are numerous, ranging from high capital investments, organization change, high costs associated with using data in the AI system, etc., all of which require organizational maturity and cultural readiness, and appropriate intelligent information technology infrastructure. Other challenges such as cybersecurity risks, accountability (including, liability and insurance practices), legal issues (regulation, law/order, etc.), technology mistrust, and the displacement of human workers should also be considered.

Following these challenges, actors in the transport and logistics sectors need to fully understand how to govern and manage risks and other aspects throughout AI systems' lifecycle, from planning and design to data collection and processing, to model development and implementation, and operation and monitoring.

At the European level, existing EU guidelines for the transportation, logistics, and supply chains sector provide important rules and ethical principles to govern and mitigate risks related to the deployment of AI technology and AI systems.

The following important steps can help organizations to manage the risks related to AI: a). Define the scope, context and actors, and criteria for the deployment of AI. b). Assess the risks at an individual, aggregate and societal level. c). Prevent and mitigate adverse impacts of these risks. d). Govern the risk management process e.g., monitoring and reviewing.

Note that these risks can be evaluated at governance and process levels by looking at whether accountability principles are respected, then at a technical level by focusing on technical risks such as robustness and performance of the systems, and finally at the underlying sub-risks that can emanate from the data used, model design, the accuracy of algorithms and statistical analysis.

Successful adoption of trustworthy AI systems in transportation and logistics sectors can be achieved by the application of clear ethical practices and value-based principles (e.g., accountability), especially in cases when AI systems are built to take decisions based on real-life incidents or events. In parallel to this, new regulation and risk management frameworks, and law-to-liability rules need to be developed (Klump and Ruiner, 2018., p. 6). In the case of smart transport where autonomous driving will be introduced soon, the ambiguities surrounding the question of which rules of engagement should be applied when an autonomous car decides to deviate from an obstacle on the road and cause a deadly accident must be solved. Also, the question of who is responsible and whom to blame (the driver who cannot interfere with the autonomous steering of the vehicle, the AI system, the production company, etc.) must be answered according to the new rules and principles.

The same applies to the logistics sector, where many important liability questions will arise when most transportation and logistics activities will be executed by autonomous systems based on machine/ deep learning algorithms that are prone to errors. In this case, and since the error lies in an algorithm, not a person, it must be clear to all parties along the logistics supply chain who will be responsible for the costs emanating from the errors of AI-based autonomous systems, such as in the case of errors related to incorrect order volumes resulting into production interruptions and unexcepted costs.

Another issue concerns the standardization, security, privacy, authentication, and authorization of the shared or harvested data that need to be regulated and internally governed by the organizations. In other words, there is a need to change the rules of the market for big data and how data is collected by organizations, public entities, and market parties (e.g., those who own the market of (big) data). This is because there exists a risk to misuse data to extract more value from users. Unless privacy and data governance are preserved by law and regulation, AI systems can cause damage and unexpected impacts of asymmetries in (market) power and access to information between organizations and organizations and individuals (for example, between employers and employees, businesses and consumers, government and citizens, etc.).

Zephyr (2020), for example, describes how Facebook was caught paying teenagers $20 per month, plus referral fees, to install spyware that let Facebook observe their online activity—including chats, videos, and even encrypted material. Participants were also asked to share their purchase histories, via screengrabs (Zephyr, 2020., p. 47). This example shows the urgency to deploy global standards and mechanisms for data governance and data management principles to protect the privacy and sensitive information and ensure the quality and integrity of the data used in AI systems, especially the data used to train the ML models.

Another important point that must be discussed here is the potential impact of AI on jobs in the transport and logistics sector as these two sectors represent a personal-intensive service industry where human-AI interaction is an important element of organizations' activities and processes.

Work and qualifications will be affected by AI technology for sure, but the level and scale of these effects are not known and, at this stage, difficult to determine. This is because AI application is not generalized to all sectors and activities, and deployment of AI technology has a long way to go before reaching the level of maturity and becoming fully institutionalized and accepted by societal organizations and individuals.

As mentioned before, the expectation is that the implementation of AI will cause the destruction of part of existing jobs as well as the displacement of certain jobs between sectors and activities. This will change the work burden of jobs and qualifications requirements in some areas by the way they will have on the labor market. Therefore, training, qualifications, and skills upgrade of existing workers is crucial to cope with the fast advances of AI in organizations, sectors, and activities.

Furthermore, the government and public authorities must start thinking about re-structuring and evaluating current education and training policies through regulatory actions to absorb the effects of automation and the deployment of AI technology, especially in top sectors such as transport and logistics sectors., energy, and security.

In this perspective, institutional coordination and regulation changes will facilitate the transition from automatization and digitalization towards the wide deployment of AI technology and systems at sectoral and organizational levels, where internal activities and processes will be affected. In transport and logistics for example, soon all documents needed to be processed along the logistics supply chain will be translated, processed, and handled automatically by AI-based systems, which will result in a significant decrease in costs and time requirements in customs, transportation, and logistics. However, to reach this, coordination among supply chain partners is required, as they must agree on standards, principles, rules, etc., and cost-sharing regimes for these services. This, in turn, requires a full understanding of actors along the logistics supply chain of the challenges and outcomes of implementing AI systems in their internal organization processes and activities. As we mentioned before these challenges and outcomes are closely related to the explainability and interpretability of AI systems, and more precisely to the principle of transparency and traceability. Both principles play a crucial role in enhancing the visibility of the logistics supply chain.

7. Concluding Remarks and Research Agenda for Mainport Logistics

This report provides an exploratory study on the development and adoption of AI in the transport and logistics sectors. Special attention is devoted to challenges and opportunities in the implementation of AI in the port and airport logistics sectors.

The fast surge of AI technology during the last two decades, aided by the advances in hardware (speed and power) and software applications (algorithms, machine learning, deep learning based on artificial neural networks), opened new possibilities in manufacturing, finance, services, education, government, healthcare, robotics, and transport and logistics.

AI enables businesses to automate processes, improve the quality of operations, and enhance production and distribution processes. However, most small and medium companies are reluctant to adopt AI technology because of the high investments and costs related to setup AI-based IT systems, but also to other reasons like the issues surrounding data sharing, standardization, compatibility, and interoperability of AI-based systems.

More generally, the adoption and impact of AI technologies in the transport and logistics supply chain sectors will depend on a wide range of factors. Companies will need to carefully consider these factors when deciding to adopt AI technology and implement it effectively. Most of these key factors are:

1. Data availability: AI algorithms can only be effective when large amounts of high-quality data are available. In the transport industry, this data can come from a variety of sources, including GPS tracking, sensor data, and customer transaction records. However, some companies may not have the resources to access and analyze it effectively.
2. Integration with existing IT systems with AI systems: This is very important as many transport companies still rely on standard IT systems and processes that may not be compatible with new AI technologies. To adopt AI technology effectively, companies need to invest in upgrading their IT infrastructure and training their employees to use new AI systems.
3. Regulation and legal rules: The transport industry is subject to a wide range of regulations and legal rules at the local, national, and international levels. Some of these regulations may restrict the use of certain AI technologies (e.g. autonomous vehicles) or may require companies to comply with strict legal rules related to specific data privacy and security standards.
4. Economic efficiency vs. social and ethical considerations: The adoption of AI technology requires significant investment and related costs to build and deploy AI systems e.g., maintenance and support costs of the systems. Companies need to be sure about the fact that they will generate sufficient revenue to cover the costs and investments in implementing the new technology. Beyond economic efficiency, the adoption of AI technology can have wide-ranging impacts on society and businesses and may raise ethical and social concerns related to privacy, safety, employment, and others bias related to social and ethical issues. In this respect, transport and logistics companies need to consider these factors when developing and deploying new AI technologies and ensure that they are aligned with broader social and ethical values.

Concerning the transportation sector, the last two decennia have been marked by an acceleration in digitalization and automation of activities and processes in this sector. This has resulted in an enormous increase in the amount of data collected through IoT devices, sensors, and other technologies. Among these new technologies, AI offers various solutions to existing challenges, that are related to operational processes, traffic management, safety, cybersecurity and privacy, policy and planning, travel behavior and demand, and employment and employment ethics.

Several AI technologies have a great impact on the transport sector, such as:

1. Autonomous and unmanned vehicles/things: Autonomous vehicles (e.g., self-driving trucks and cars), delivery drones Unmanned Aerial Vehicles (UAVs), and Personal Aerial Vehicles (PAVs) are rapidly developing technologies that could transform the transport and logistics industry. By removing the need for human drivers, autonomous vehicles could improve safety, reduce costs, and increase efficiency in the supply chain.
2. AI-based traffic management support systems: AI will play a crucial role in planning applications by improving decision support for transport planning.

3. Real-time traffic management optimization and coordination: AI applications are already being used in control functions applications, automatic detection, and image processing for traffic data collection. clustering application to the identification of specific drivers based on behavior, and optimization application to optimal traffic networks.
4. Incident management: AI technology and applications are used to predict traffic demand modeling and incident management on road networks.
5. Asset management and maintenance: AI is used to develop an optimal work plan for maintenance, by helping to detect failures, defects, and potential downfall of machines and equipment.

In the logistics and supply chain sector, AI is considered a breakthrough in the development of the future smart logistics supply chain. AI provides the logistics sector with various opportunities to bring end-to-end visibility, and improve the efficiency of activities and processes, like for example the improvement of real-time decision-making and planning using predictive analytics, predicting traffic demand, dynamic route guidance, automating warehouses, predictive maintenance and automatic incident detection, among other things. However, the successful implementation of AI technology and systems in the logistics sector requires close collaboration between all parties along the logistics supply chain networks, especially in collecting, using, and sharing data and information.
More generally, the most important application domains of AI technology in the logistics sector are the following:
1). Logistics planning and intelligent route optimization: AI can be used in planning and fleet management, which enables companies to real-time track the position of vehicles and goods, predict travel time and mileage, help in determining routing choice/route optimization, number of needed vehicles, travel costs, use of fuel, etc. AI systems can help companies to improve route optimization and planning of shipments, from pick up of shipments up to the last mile.

2). Automated warehouses and warehouse management: AI has already proven to be a very effective technology in helping companies to set up fully automated warehouses. Automated warehouses can exploit real-time data for predictive modeling, automated classification and identification of goods, and tracking, managing, and monitoring inventory levels through each step in the transportation and delivery process. This reduces significantly the costs related to human errors and increases speed and accuracy when picking orders. As result, customer satisfaction rates improve, and hence, business revenue. Note that automated warehouse management is based on the integration of AI with robotics technology. Robotics has the potential to automate many of the manual tasks involved in the supply chain, such as sorting, packing, and loading/unloading goods. By using robots for these tasks, transport, and logistics companies could reduce costs, increase efficiency, and improve safety.

3). Predictive analytics and predictive logistics: Data collection, classification, analysis, and application of predictive intelligence analytical tools, whether through synchronization with AI platforms or not, become more and more standardized into businesses' IT systems. Predictive analytics involves using machine learning algorithms to analyze historical data and make predictions about future outcomes. In the context of transport and logistics, predictive analytics is used to forecast demand, optimize routing and scheduling, dynamic planning, and identify potential bottlenecks or delays in the supply chain.

4). Back Office AI and natural language processing: with the digitalization of many back-office processes, manual processing and controlling tasks of documents were replaced by automated document processing and digital exchange of documents. Nowadays, most logistics companies are using intelligent business process automation that combines AI, robotic process automation (RPA), process mining, and other technologies to further automate back-office tasks.
Natural language processing (NLP) is becoming the standard AI technology when dealing with the interaction between computers and human language. Online shopping, E-commerce, and other marketing and commercial activities have much of this AI technology in the background of their systems e.g., AI-driven recommendations are a powerful business driver nowadays.
In the context of transport and logistics, NLP could be used to automate customer service interactions, facilitate communication between

stakeholders in the supply chain, and analyze unstructured data sources (e.g., social media posts) to gain insights into customer sentiment or market trends.

Overall, the AI technology with the greatest impact on the logistics supply chain sector will depend on a variety of factors, including the specific needs of the industry, the availability of data and resources, and the level of investment in research and development. However, the applications of AI technology listed above are likely to be among the most important in the years to come.

Zooming now on the case of implementation of AI technology in ports and airports sectors, this study shows that the transition from partial integration of AI technologies in digitalization and automation of ports and airports to full implementation of AI technology will have a tremendous impact on the development of intelligent ports and airports of the future. For example, using AI algorithms to optimize processes, ports, and airports can increase efficiency and productivity, and reduce the time and resources required to handle cargo, process baggage, and manage passenger flows.

In terms of efficiency and cost reduction, the adoption of AI technology in ports and airports activities will improve their competitiveness, efficiency, safety, sustainability, and international position in a rapidly changing global economy.

In terms of safety and environmental issues, AI can help to reduce environmental footprint by reducing waste, energy consumption, and emissions, but also helping the ports and airports to detect potential security threats, monitor critical infrastructure, such as runways or port facilities, reduce the risk of accidents and improve time response in case of emergencies.

In the case of the maritime sector and port activities, the adoption of AI technology and AI-based optimization algorithms and machine learning models will improve the accessibility and connectivity of the ports by integrating port logistics activities with inter- and multi-multimodal transportation networks.

Currently, most global ports use real-time data exchange platforms, based on the development of IoT, intelligent sensing and imaging technologies, intelligent cameras, etc. The adoption of AI will add new capabilities to existing port systems through the implementation of AI models and algorithms, such as voyage optimization and predictive maintenance of port equipment, advanced operational control processes (AGVs, automated (un) loading cranes), and the possibility to help in decision-making.

The key application areas where AI technology is expected to revolutionize future port operations and port logistics activities are:

1). Smart shipping: the development of fully autonomous ships is still in the design and test phase. In case the autonomous ships will be developed and implemented, ports need to think about the changes in the corresponding port infrastructure that will be needed to accommodate smart ships, especially in building new port systems supporting the AI-based intelligent systems that integrate AI with IoT and other intelligent transport and logistics systems.

2). Optimization of container Terminal Operations: AI algorithms can be used to optimize container terminal operations by improving the scheduling and routing of trucks and ships. By analyzing data on shipping schedules, container volumes, and equipment availability, AI algorithms can optimize the use of resources and reduce congestion at the terminal.

3). Smart port logistics: AI can be used to deploy advanced digital platforms to coordinate port-logistic operations of cargo across multimodal transport and logistics nodes. When AI is integrated into existing digital platforms, ports can then easily build complex system-of-systems digital platforms that will help to predict future operational scenarios and anticipate potential incidents, bottlenecks, and disruptions. The application of advanced ML/DL models, predictive modeling algorithms, simulation techniques, and digital twins' decision support tools, will help the ports to fully take advantage of real-time visualization, simulation, and advanced analytics capabilities to take the right decisions to improve port operations and planning.

4). Port Traffic Management and operational planning: AI algorithms can be used to optimize port traffic management by providing real-time recommendations to port operators on how to optimize traffic flows and reduce congestion. By analyzing data on shipping schedules, truck routes, and road conditions, AI algorithms can provide real-time guidance on the most efficient routes to and from the port. At the operational planning level, AI can improve the decision support systems in planning, execution, and control. The application of ML algorithms can provide port terminal authorities with a powerful tool to predict potential disruptions and delays in port operations, and, based on these predictions, port terminal authorities can take appropriate decisions to prevent disruptions. This will allow them to apply better policies for asset management and equipment utilization in the port.

5). Cargo tracking and self-learning algorithms: AI algorithms can be used to improve cargo tracking and tracing by providing real-time updates on the location and status of cargo. By analyzing data on shipping schedules, container movements, and cargo status, AI algorithms can provide real-time visibility into the location and status of cargo, increasing the efficiency of port operations and logistics processes, and reducing the risk of lost or delayed shipments. Also, AI systems, based on machine learning, will help ports to develop robust and self-learning predictive models that are capable to adapt to changes in the port environment e.g., fully predictable ports.

6). Smart asset management and maintenance: The most important AI application in asset management is computer vision where data and classified information are retrieved from images or videos to estimate the condition of an asset or equipment. AI algorithms can be trained to detect anomalies or deviations in an asset or equipment (e.g., machines, engines, devices, etc.), using supervised and non-supervised machine learning models. AI algorithms can also be used to optimize vessel maintenance schedules and reduce downtime. By analyzing data on vessel performance, maintenance records, and shipping schedules, AI algorithms can predict when maintenance will be required and schedule it proactively to minimize disruption to shipping schedules.

Finally, concerning the application of AI technology in the aviation industry and air transport logistics, this study shows that most airports are taking a keen interest in emerging technologies, more specifically the potential adoption of AI technology such as machine learning and deep learning, to increase the levels of automation, cyber-secure data sharing and connectivity in air traffic management as well as the application of AI-based intelligent systems in streamlining air business processes and improve customer service provision, maintenance, engineering, and prognostics.

The adoption of AI technology in aviation holds great opportunities for the air transport and airports sector to improve the efficiency of airport operations, safety, passenger experience, air traffic services, optimization of air traffic management network services and airport infrastructure, while also reducing costs, enhancing sustainability, building resilience to disruptions, and cope with changes in air demand and increasing complex air traffic and infrastructure capacity.

Air traffic management is increasingly adopting advanced automation based on AI in effectively optimizing flights journey and air traffic control systems, helping with intelligent maintenance, improving airline safety, and airport decision-making through airport cooperative decisions. For example, machine learning algorithms are applied to enhance the monitoring system of the gas turbine during flights, increase safety when an airplane is landing, or check the engine on board.

The most important application areas of AI technology in air transport and airports logistics operations can be summarized as follow:

1. Air traffic management: AI applications and algorithms can be used to optimize air traffic management and reduce delays. By analyzing data on flight schedules, weather patterns, and air traffic volumes, AI algorithms can provide real-time recommendations to air traffic controllers on how to optimize air traffic flows and reduce delays.

2. Passenger flow management and baggage handling: AI algorithms can be used to monitor passenger flows through an airport and identify

potential bottlenecks or congestion points. By analyzing data on passenger volumes, flight schedules, and security checkpoint wait times, AI algorithms can provide real-time recommendations to airport staff on how to optimize passenger flows and reduce wait times. AI can be applied in baggage handling, using AI algorithms to optimize the routing of baggage through an airport's baggage handling system. By analyzing data on flight schedules, passenger volumes, and baggage loading times, AI algorithms can optimize the routing of baggage to reduce wait times and minimize the risk of lost baggage.

3. Security Screening: AI algorithms can be used to enhance security screening at airports. For example, AI algorithms can be used to analyze images from X-ray machines to detect potential threats, such as weapons or explosives, that may not be visible to human screeners.

4. Aircraft Maintenance: AI algorithms can be used to optimize aircraft maintenance schedules and reduce downtime. By analyzing data on flight schedules, maintenance records, and aircraft performance, AI algorithms can predict when maintenance will be required and schedule it proactively to minimize disruption to flight schedules.

Various practical use cases and pilot projects were presented and discussed in this report which gives a good overview of the application of AI technology in aviation and airport operations management and traffic management.
In summary, future applications of AI technology can help the aviation sector and airports to develop a smart airport intelligent system that integrates airport operations management and air traffic management with advanced and seamless multi-modal transportation systems from door-to-door passenger travel journeys.
As a concluding remark of this chapter, it is worthy to mention that the exist significant risks of AI bias must be solved to gain more trust in the adoption of AI technology in society. Existing concerns about privacy, data sovereignty, fear of losing power, an increase in inequality, the complexity of technology, and fairness to control it are fully legitimate. In this context, the focus of AI researchers and AI designers, and developers on making AI technology and systems more ethical, robust, secure, explainable, and responsible can help to gain trust in AI technology among people. However, there is a need to develop an ethical guidance framework to solve the legal, social, economic, organizational, and technological related challenges that are posed by the AI bias and misuse of AI technology. Such ethical guidance frameworks must be based on clear rules, principles, and protocols concerning the privacy and autonomy of individuals, ethical code of conduct, and justice.

7.1. Research agenda for Mainport Logistics

Based on the discussions and findings of this study, we propose a few potential research topics on the application of AI technology in transport and logistics, especially Mainport logistics (e.g., ports and airports) that might help to set up new research agenda and help to identify potential topics for research proposals.

First, for both the ports and airports, there is a need to investigate the impacts of the integration of AI technologies in the port logistics operations and the air transport operations with smart interconnected multimodal transport platforms and services, that enable real-time collaboration between ports and airports and other transportation modalities, for efficient passengers and freight flow management. A centered and integrated approach of interconnected AI with other systems, based on passenger and goods flow, into smart multimodal transport hubs, can pave the way for the development of an advanced seamless door-to-door connectivity of mainports.

Second, the implementation of AI-based information management systems for a seamless multimodal transport system requires synergies between transport modes and air/sea transportation in facilitating and stimulating data sharing for a seamless door-to-door journey and improvement of planning and operations activities.

Third, the development of AI-based blockchain platforms to improve operations of ATM and port operations is another research topic that needs more investigation, especially the causes and underlying factors that hamper the collaboration between parties along the logistics supply chain. Close to this research topic, the why/methods AI technology, especially eXplainable Artificial Intelligence (XAI) algorithms, is designed and applied in predicting demand and traffic flows need to be assessed concerning transparency, explainability, and trustworthiness of AI-based automated systems.

Fourth, the increasing application of advanced automatic speech recognition software, based on deep learning and deep neural networks, is becoming part of business communication activities, also in airports and ports e.g., communication between the controllers and ships/pilots. However, few numbers of research have been done to better understand the type of human-machine automation that best suit existing communication systems, by looking at how much AI should be used, where it would be most beneficial, and whether it should perform tasks autonomously or serve as a tool to support the human's decision-making.

Finally, many questions can be raised about the application of predictive AI into existing human-driven traffic and planning systems in transport and logistics sectors and ports and airports operations for better decision support, especially predicting unexpected changes or events ahead of time.

Based on what has been said, here are some important research questions that could be relevant for future research:

1. How can AI-based systems be integrated into system-of-systems, where AI, IoT, simulation, and advanced modeling techniques are combined, to solve operational challenges in transport and logistics, including ports and airports, at strategic and operational management levels?

2. What are the technical challenges associated with AI adoption in transport and logistics sectors, including ports and airports, concerning data collection, and integration with existing systems, while ensuring system reliability and safety?

3. What are the best fields of application of AI-based models of machine learning and deep learning that help to achieve the best outcomes in terms of optimization of port/airport operations and processes, like optimizing planning (ETA, ETD), cargo handling, freight and baggage processing, passenger flow management, consumer services, etc.?

4. What are the potential costs and benefits of AI adoption to improve the efficiency of logistics processes in ports and airports, in terms of traffic flows, infrastructure, security (detection and prevention) and safety, reducing costs, and increasing revenue?

5. What are the potential social and ethical implications of AI adoption in transport and logistics/ports and airports, and how can these be addressed to ensure that this technology is developed and deployed in a way that is ethical and aligned with broader social values?

6. How can AI be used to improve the environmental sustainability of ports and airports, including reduction of congestion and GHG emissions, improving energy efficiency, and minimizing waste?

7. How can actors from different domains and societies work together to develop and deploy AI technologies in a way that maximizes the potential benefit for everyone, while minimizing potential risks and unintended consequences?

8. What are the advantages and disadvantages of integrating AI technology and systems into the digital twin systems for monitoring, decision-making, and predictive analytics?

9. How can the application of AI technology help airports to develop future smart airports based on the integration of intelligent airport

operations systems with advanced and seamless multi-modal transportation systems from door-to-door passenger travel journeys?

Note that the above specific research questions will depend on the specific context and objectives of the research, as well as the unique challenges and opportunities associated with AI adoption in the transport and logistics sectors.

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Appendx 1. List of Interviewed experts

1). Interview met Jan Egbertsen (PoA): 20 Dec. 2022. AI in de Haven

2). Interview met Hoogendoorn, R.G. (Raymond), Lector AI (HR): Tuesday 24 January 2023

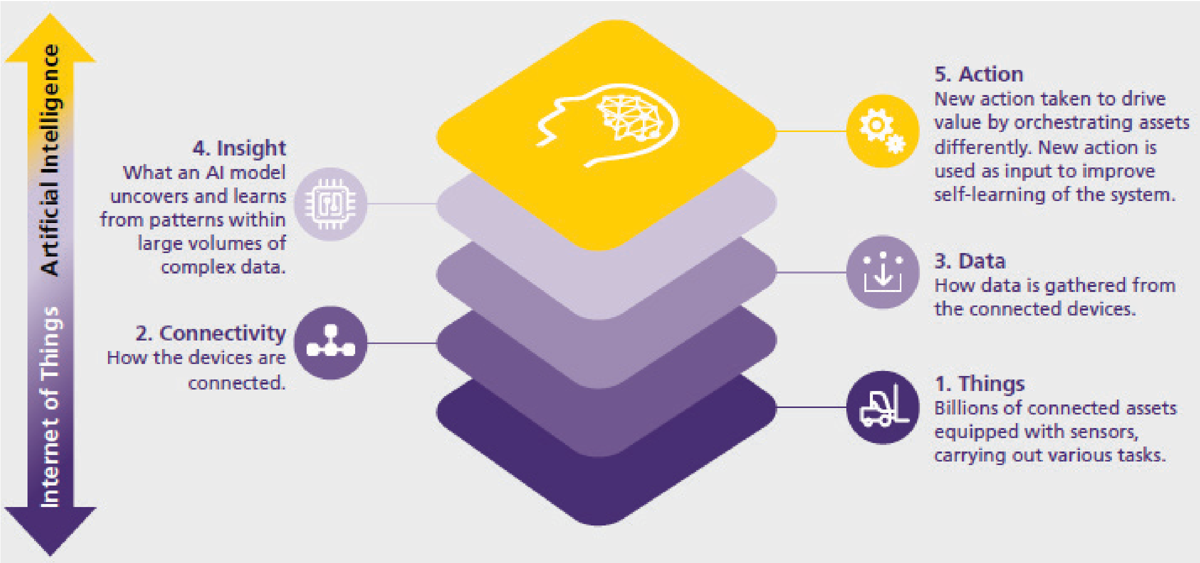
3). Interview met Dennis Moeke (Lector HAN): Thursday 26th January 2023

4). Interview met Jurjen Helmus (HvA): Wednesday 8th February 2023

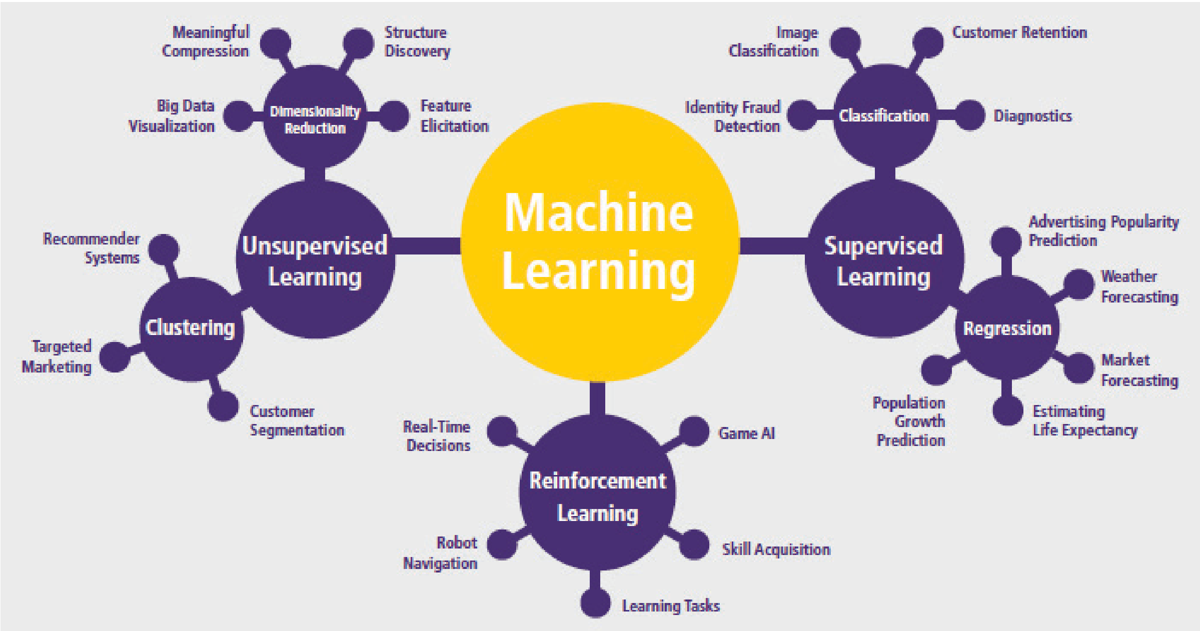
5). Interview PicNic's CTO-Technology "Daniel Gebler" (by Jurjen Helmus (HvA), Datalog Podcast interview about AI in retail): Wednesday 8th February 2023

Appendix 2. Key Components of AI systems and Taxonomy of Machine learning methodologies

Key components of AI systems



Taxonomy of Machine Learning Methodologies



Source of figures: Gesing, B; Peterson, S. J; Michelsen, D., 2018. Artificial Intelligence in Logistics. DHL/IBM joint report. DHL Customer Solutions & Innovatio (pp-7-8).