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Measuring the Sustainability Impact of Artificial Intelligence in Logistics: A Case Study Analysis

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Abstract

Sustainability in logistics entails reducing environmental and societal impacts while meeting the growing demand for goods and services. Artificial Intelligence (AI) solutions offer a potential avenue for achieving this goal. This work aims to analyze methods for assessing the sustainability impact of AI in logistics, focusing on environmental, social and economic impacts.

Sustainability is increasingly important for supply chains and companies are adopting sustainable practices to improve their reputation, attract environmentally conscious consumers and meet stakeholder demands. Investors are also increasingly interested in companies implementing sustainable practices due to higher growth potential and reduced risks.

AI can optimize several aspects of logistics, such as transportation, inventory management, warehouse management and delivery. Benefits of AI in logistics include vehicle routing optimization, improvements in truck utilization, real-time route adjustments, risk and hazard identification and predictive maintenance.

Evaluating the sustainability improvements brought about by AI in logistics is crucial for several reasons. It can aid in identifying potential benefits and drawbacks of AI solutions, inform decision-making, contribute to more sustainable logistics practices and inform policymaking. The KPIs for the evaluation of sustainability in logistics found in the literature, may not provide a complete picture of AI's impact on sustainability, so companies should use a more comprehensive and integrated approach that takes into account a wider range of sustainability factors, including those specifically related to AI technology. Interviews with four Italian companies reveal that measuring the sustainability impacts of AI solutions is not yet a priority. Barriers include the lack of integration between systems and processes, the need for advanced technologies and analytics, the development of data governance frameworks and changes in the company organization. Additionally, there may be a limited incentive to invest in measuring sustainability benefits unless they are financially relevant to companies.

Measuring the sustainability impacts of AI solutions in logistics may require time and effort but is essential for creating more sustainable and responsible businesses.

Key-words: Artificial Intelligence, Logistics, Sustainability, Measurement, Indicators

Abstract in italiano

La sostenibilità in ambito logistico implica una riduzione degli impatti ambientali e sociali, soddisfacendo la domanda crescente di beni e servizi. L'Intelligenza Artificiale rappresenta una potenziale soluzione per raggiungere questo obiettivo. Questo elaborato mira ad analizzare i metodi utilizzati dalle aziende per valutare l'impatto sugli aspetti di sostenibilità ambientale, sociale ed economica dell'utilizzo di soluzioni di IA in ambito logistico. La sostenibilità delle Supply Chain è sempre più rilevante e le aziende adottano pratiche sostenibili per migliorare la loro reputazione, attirare consumatori sempre più interessati a queste tematiche e soddisfare le richieste degli stakeholder. Anche gli investitori sono sempre più interessati ad aziende sostenibili per il loro maggior potenziale di crescita e una riduzione dei rischi a cui sono esposte. L'IA, inoltre, è in grado di ottimizzare molti aspetti della logistica come la gestione dell'inventario, la gestione del magazzino, il trasporto di merci e la consegna di queste. Alcuni esempi di vantaggi portati dalle soluzioni di IA sono l'ottimizzazione dei percorsi dei veicoli per le consegne, l'ottimizzazione della saturazione dei veicoli, l'adeguamento dei percorsi in tempo reale, l'identificazione di rischi e la manutenzione predittiva, riducendo costi, emissioni inquinanti e rifiuti prodotti.

Risulta quindi fondamentale riuscire a valutare l'impatto di queste soluzioni sulla sostenibilità. In prima istanza può aiutare ad identificare i potenziali benefici e svantaggi dell'utilizzo di soluzioni di IA, può consentire alle aziende di prendere decisioni basate su dati oggettivi, può contribuire all'implementazione di pratiche più sostenibili in ambito logistico e ad una migliore legislazione in materia di sostenibilità. I tradizionali indicatori utilizzati per misurare la sostenibilità in ambito logistico, per quanto in grado di valutare almeno parzialmente i benefici portati dalle soluzioni di IA, non forniscono un quadro completo. Le aziende dovrebbero quindi utilizzare un approccio più completo per analizzarle. Le interviste con quattro aziende italiane hanno rivelato che la misurazione dell'impatto dell'IA sulla sostenibilità non è effettuata e non è una priorità. Gli ostacoli riguardano la mancanza di integrazione tra i sistemi aziendali, la necessità di tecnologie avanzate, lo sviluppo di pratiche di data governance più avanzate e la necessità di modifiche nell'organizzazione aziendale. Inoltre, gli investimenti in queste tecnologie non sono incentivati a meno che non risultino economicamente rilevanti per le aziende. La misurazione dell'impatto sulla sostenibilità delle soluzioni di IA, richiede un tempo lungo e sforzi rilevanti per le aziende, ma è necessario per adottare pratiche più sostenibili e responsabili.
Parole chiave: Intelligenza Artificiale, Logistica, Sostenibilità, Misurazione, Indicatori

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1 Introduction

From a global scope, the logistics industry is an essential component of the global economy, with billions of goods and products being transported worldwide every day.

However, this industry also has significant environmental and social impacts, which can have adverse consequences for the planet and society.

One of the most significant environmental impacts of the logistics industry is greenhouse gas emissions. The transportation of goods and products is responsible for a substantial portion of global emissions, which cause climate change and other environmental problems. In addition, the industry may generate waste such as packaging materials, excess inventory and discarded products, which can harm the environment and contribute to landfill waste.

Moreover, the logistics industry also has social impacts, including labour practices and worker's safety. The industry's global reach and reliance on complex supply chains can make it challenging to ensure that workers are treated fairly and that working conditions are safe. Also, the transportation of goods and products can have a significant impact on local communities, such as increased traffic congestion, noise pollution and other environmental impacts.

Both the environmental and social perspectives are two of the three key pillars of Sustainability (Figure 1).

In the logistics industry, sustainability means reducing the negative impact on the environment and society while still meeting the growing demand for goods and services. This is a challenging task, given the increasing complexity and scale of the industry. However, the emergence of Artificial Intelligence (AI) solutions has provided a potential solution to this problem.

Figure 1: Three Pillars of Sustainability

(Source: www.nextlevelpurchasing.com/blog/3-pillars-and-benefits-of-sustainability.html)

The aim of this work is to conduct an analysis of the various methods that are currently used to assess the sustainability impact of the use of artificial intelligence in logistics. The following chapters analyze the existence and the effectiveness of these methods in accurately measuring the environmental, social and economic impacts of AI in logistics and identify any gaps or limitations in the current approaches. Ultimately, the goal is to provide insights and recommendations for improving the assessment and evaluation of the sustainability impact of AI in logistics, in order to facilitate the development of more sustainable and responsible logistics practices.

From the literature review emerges how, in recent years, there has been a growing demand for sustainability in supply chains driven by various stakeholders. As a result, companies are adopting sustainable practices to improve their reputation, attract more environmentally conscious consumers and meet stakeholder demands.

In addition to the benefits of improved reputation and stakeholder satisfaction, investors are increasingly interested in companies implementing sustainable practices due to their growth potential and reduced risks. Therefore, sustainability is becoming a key factor in investment decisions and companies that prioritize sustainability are likely to attract more investment.

In the context of logistics, AI can be used to optimize various aspects of the supply chain, such as transportation, inventory management and delivery. By leveraging AI solutions, companies can reduce waste, improve efficiency and minimize their environmental footprint.

Artificial intelligence can help improve logistics efficiency and effectiveness by analyzing large amounts of data generated by logistics activities and has many potential applications in logistics, such as vehicle routing optimization, truck utilization improvement, real-time route adjustments, risk and hazard identification and predictive maintenance.

For example, AI can optimize vehicle routing by considering factors such as traffic conditions, delivery schedules and the location of distribution centers. This can lead to reduced fuel consumption, lower emissions and improved delivery times. AI can also help with truck utilization by optimizing the load capacity and minimizing empty miles, reducing the number of trips needed and associated emissions.

Furthermore, AI can identify and address potential risks and hazards, such as accidents, breakdowns, or weather-related delays, in real-time, allowing logistics providers to take proactive measures to minimize disruptions and ensure on-time delivery.

Another application found in the literature is the optimization of warehouse operations and inventory management. For instance, AI can predict demand and optimize inventory levels, reducing waste and unnecessary transportation, further improving the sustainability performance of companies.

While AI is acknowledged for enhancing efficiency, reducing costs and improving overall productivity in logistics operations, it is essential to establish a methodology for evaluating its impact on sustainability. Indeed, understanding how companies evaluate the sustainability improvements brought about by the application of AI in logistics is crucial for various reasons.

Firstly, it can aid in identifying the potential benefits and drawbacks of AI solutions concerning sustainability, which can inform decision-making and contribute to developing more sustainable logistics practices. It can enable companies to better comprehend the environmental, social and economic impacts of their AI solutions, which can facilitate the creation of more effective sustainability strategies. It can also inform the development of evaluation frameworks that can be used to assess the sustainability impact of AI solutions in logistics, which can contribute to establishing standards and guidelines for sustainable logistics practices. Lastly, it can inform policymaking by providing insights into the effectiveness of existing regulations and incentives for promoting sustainable logistics practices and identifying areas where new policies and incentives may be required.

The evaluation of the sustainability performance of AI solutions in logistics is therefore an important area that requires attention from researchers and practitioners. While literature is present on methods for evaluating the sustainability impact of logistics operations, including transportation and warehousing, there is a lack of research on how these methods can be applied to companies that are implementing AI solutions in their logistics operations.

By limiting the ability of companies to evaluate the sustainability impact of their AI solutions and make well-informed decisions concerning their logistics operations, the presence of this research gap holds significant importance.

While traditional KPIs used in logistics can be applied to AI solutions, they may not provide a complete picture of their impact on sustainability. This is because these solutions may have both positive and negative sustainability impacts that are not captured by traditional KPIs.

To evaluate the sustainability performance of AI solutions in logistics, companies should then use a more comprehensive and integrated approach, which can provide a more complete picture of the sustainability impact of AI solutions and help companies make informed decisions about their adoption.

To fill the gaps found in literature four different Italian companies were interviewed. The focus of the interviews was on companies that had either implemented AI solutions to improve their logistics operations or developed AI solutions for logistics. These companies may be interested in measuring the sustainability implications of their solutions for marketing purposes or need to assess the sustainability impact of the solutions they have applied. To conduct the interviews, a semi-structured interview guide was developed based on the research questions, which included questions about the companies' approach to evaluating sustainability in logistics, their experience with AI in logistics and the AI algorithms used by their applications.

From the interviews, it appears that companies in the Italian industry have yet to prioritize the measurement of sustainability impacts of their AI solutions. There are several reasons for this, including the lack of integration between different systems and processes within organizations, the need for advanced technologies and analytics, the development of data governance frameworks and significant changes in the companies' organization. Additionally, there may be limited incentives to invest in measuring sustainability benefits unless they are financially relevant to clients.

Moreover, companies' current focus seems to be on implementing and operating AI solutions rather than considering their sustainability implications. As a result, the measurement of the sustainability impact of AI solutions in logistics appears to be a distant objective for many Italian companies.

To overcome these barriers, companies may need to prioritize the integration of systems and processes and invest in advanced technologies and analytics. But most importantly they need to shift their focus from solely implementing and operating

AI solutions to also considering their sustainability implications. Ultimately companies estimate that to be able to measure the sustainability impacts of AI solutions in logistics may require over a decade, but it is an essential step towards creating more sustainable and responsible businesses.

2 Literature Review

This section introduces the most important theoretical concepts and literature background related to the topic. Section 2.1 proposes an overview of the literature about the use of Artificial Intelligence in logistics and its sustainability implications, Section 2.2 draws an outline of the main KPIs used to measure the sustainability performance of logistics, Section 2.3 proposes an overview of the main algorithms found in literature and about the performances and the results of the different algorithms when applied to different logistics problems.

2.1. AI's sustainability implications in logistics

2.1.1. Artificial Intelligence and Sustainability

To analyze and study methods to quantify the sustainability impact of Artificial Intelligence (AI) in the logistic sector, a brief literature review on the topic has been carried out.

In general, both positive and negative impacts of AI on sustainable development have been reported. Evidence shows that AI may act as an enabler on 134 out of the 169 Targets associated to the 17 Sustainable Development Goals adopted by the UN in 2015. These positive effects are obtained mainly through a technological improvement, which may allow to overcome certain present limitations. However, 59 targets (35%) may experience a negative impact from the development of AI [41].

If not used carefully AI may lead to an increase in inequalities due to the additional qualifications needed for any job and its use in regions where democratic control, transparency and democracy are lacking may facilitate the development of nationalisms. The AI algorithms used by social media and traditional media tend to create the so-called Echo Chambers, environments in which a person will only encounter information and opinions that reflect their own. This may reinforce the biases and beliefs of single communities and lead to the development of isolated communities with extreme views. Furthermore, the manipulation of the algorithms used by social media may influence the outcome of elections, steer public opinion and undermine freedom of speech. Algorithms could be trained to recognize and categorize diversities and may be used to discriminate and emarginate certain groups of people based on race, ethnicity, or religion. However, also algorithms uncritically trained on regular news articles may learn and reproduce discriminations and societal biases against women and minorities [41]. AI has the potential to automate many tasks currently performed by humans, which could lead to job displacement. However, AI could also create new jobs in areas such as data analysis and software development, allowing humans to transition to less physically demanding and strenuous jobs.

From an environmental point of view advanced AI technology and research require massive computational resources that are often only available through large computing centers. These facilities have a significant energy requirement and carbon footprint, which can contribute to environmental degradation.

The benefits cover all the three main areas of sustainability: Environmental, Economic and Social.

From the environmental and social point of view AI can certainly act as an enabler for achieving targets related to food, health, water and energy services. AI-powered systems can help optimize agricultural practices, by analyzing the terrain or from pictures of the crops, can improve healthcare, monitor water quality and increase energy efficiency. Moreover, it can play a crucial role in building low-carbon systems by enabling the creation of circular economies and smart cities. These systems can help reduce waste, increase resource efficiency and minimize carbon emissions. For example, AI-powered waste management systems can help identify materials that can be recycled or reused, and smart city systems can optimize energy usage based on real-time data.

AI can also support the integration of renewable energy sources into the grid by enabling smart grids that can match electrical demand to times when renewable sources are available. This can help increase the reliability and scalability of renewable energy systems. Furthermore, it can help identify areas of poverty and foster international action using satellite images. By analyzing satellite imagery, AI can help identify areas that lack access to basic services such as healthcare, education and clean water. This information can be used to target interventions and allocate resources more effectively. AI also has the potential to allow companies to greatly improve their efficiency by improving their operations and this will inevitably lead to a reduction in waste and pollution.

From the economic point of view AI can improve efficiency and productivity in various industries, including retail, manufacturing and logistics, helping companies cut costs and reducing the amount of resources needed for their operations. AI algorithms can analyze large datasets and provide insights that can help businesses take better decisions, optimize processes and reduce costs leading to a more sustainable economic performance in the future.

Another critical aspect that emerges from literature is the fact that AI applied for sustainable development is widely affected by external stakeholders and to result in major changes in performances a large amount of costs would be paid to implement measures related to AI and sustainable development. These costs might damage the economic performance of the companies in the short term, but could enhance the image and product competitiveness, after long-term implementation, to further promote the economic performance. [30]

The increasing demand for sustainability in supply chains is driven by a variety of stakeholders, including consumers, social activists and non-governmental organizations. These stakeholders are pushing for companies to adopt more environmentally friendly and socially responsible practices in their supply chains.

In [15] and [31] the authors underline how, implementing sustainable practices in their supply chains, companies can improve their reputation, attract more environmentally conscious consumers and meet the demands of stakeholders who value sustainability. As a matter of fact, consumers which are concerned about the impact of their purchasing decisions on the environment will be more likely to buy from companies which are implementing sustainable practices, moreover, environmentally conscious consumers are usually willing to pay a premium leading to improved revenues.

In recent years also investors are paying attention to the sustainability of the companies they want to invest in. Companies implementing sustainable practices are seen as more forward-looking and with a higher growth potential, avoiding risks of supply chain disruptions or problems associated with regulatory compliance. Therefore, the interest of shareholders towards sustainable companies is growing.

Hence, companies are striving to identify and implement more sustainable solutions for their supply chains.

2.1.2. Artificial Intelligence in Logistics

The integration of Artificial Intelligence (AI) in logistics is a rapidly evolving field that has the potential to transform the way goods and services are transported, stored and delivered. The logistics sector is under immense pressure to keep up with the demands of consumers and businesses and AI can help to optimize various logistics operations, such as forecasting, inventory management, route optimization and real-time tracking. This chapter proposes a brief introduction on the application of AI in logistics, the main problems identified in literature and a focus on the sustainability implications of the usage of Artificial intelligence in the logistic sector.

In [44] the authors have identified seven clusters that can be amalgamated to a conceptual framework for the application of AI, ML and DL in Smart Logistics in industrial enterprises, namely:

1. "Strategic and tactical process optimization", focuses on using AI, ML and DL to optimize business processes at an enterprise or network design level. The goal is to provide not just data, but also useful information and insights for making strategic and tactical decisions.
2. "Frameworks for Cyber Physical Systems (CPS) in logistics", focuses on the development from traditional to smart logistics systems using actors, sensors and advanced learning approaches for real-time data analysis. The goal is to use this data to improve production and logistics processes in fields such as predictive maintenance, quality control and logistics, utilizing cloud computing. This leads to improved quality in production and logistics processes.
3. "Predictive maintenance", focuses on using AI, ML and DL to optimize predictive maintenance in production and logistics processes. It studies the use of learning methods for continuous monitoring and reporting of machine states and quality parameters. The aim is to make proactive maintenance decisions based on real-time data analysis.
4. "Hybrid decision support systems", focuses on improving human-centered decision-making by using AI, ML and DL technologies to collect, aggregate and pre-analyze decision-relevant information. It aims to outperform purely rational decision-making processes.
5. "Production planning and control systems", focuses on the application of advanced planning and control approaches in the research fields of inventory management and flow shop problems.
6. "Improvement of operational processes in logistics", focuses on the application of AI, ML and DL technologies to enhance operational

processes in logistics. The cluster outlines various possibilities for improvement, including the use of swarm robotics to optimize smart warehouses or AI-based algorithms for the optimization of vehicle routing in logistics problems.

7. "Intelligent Transport Logistics", focuses on the application of AI, ML and DL technologies in intelligent transport systems and transport processes. The aim is to increase the performance of transport logistics by applying AI methods combined with IT, data communication, electronic sensing, GPS and GIS.

Focusing on cluster 6 and 7, different problems emerged. For what regards vehicle routing and its optimization, the research identified four main problems addressed using AI in literature.

1. Traveling Salesman Problem: The Traveling Salesman Problem (TSP), presented in Figure 2, is a classic optimization problem in which a salesperson must visit a set of cities in the least possible distance and return to the starting city. The goal is to find the shortest possible route that visits each city exactly once and returns to the starting city.

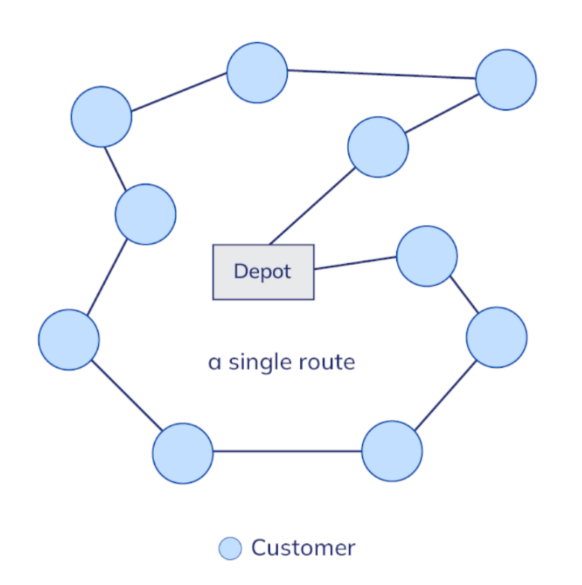

Figure 2: Travelling Salesman Problem

(Source: nextbillion.ai, "End-to-End Route Optimization API: Vehicle Routing Problem Solver for Mobility-Driven Businesses")

2. Vehicle Routing Problem: The Vehicle Routing Problem (VRP), represented in Figure 3 is a combinatorial optimization problem that involves finding

the most efficient routes for vehicles to visit a set of customers. The VRP is a more general problem than the TSP and includes additional constraints, such as vehicle capacity and the number of available vehicles. The goal is to find the most efficient routes that meet customer demand while minimizing the total distance traveled and the number of vehicles used.

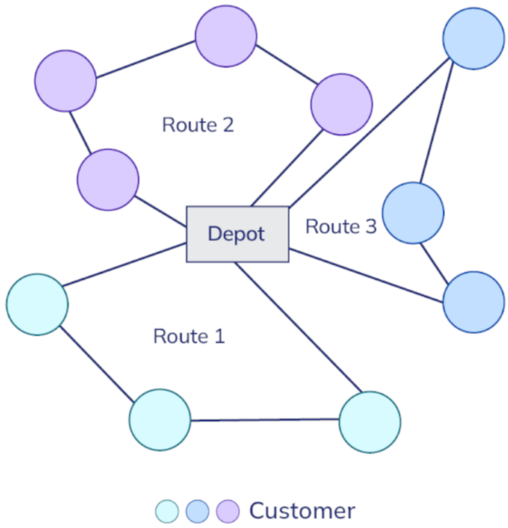

Figure 3: Vehicle Routing Problem

(Source: nextbillion.ai, "End-to-End Route Optimization API: Vehicle Routing Problem Solver for Mobility-Driven Businesses")

3. Vehicle Routing Problem with Time Windows: The Vehicle Routing Problem with Time Windows (VRPTW) extends the VRP by adding time windows for each customer. This means that each customer must be visited within a specified time frame.
4. Pickup and Delivery Problem with Time Windows: The Pickup and Delivery Problem with Time Windows (PDPTW) is an extension of the VRPTW that involves the pickup and delivery of goods. The PDPTW adds the constraint of transporting goods between customers, making the problem more complex. The goal is to find the most efficient routes that meet customer demand, transport the goods and minimize the total distance traveled and the number of vehicles used, while taking into account the time windows for each customer and the capacity of the vehicles.

2.1.2.1. Sustainability Implications

The transportation sector is responsible for a significant portion of the world's CO_2 emissions due to the use of fossil fuels such as gasoline and diesel. The shipping of goods contributes to this trend, as the transportation of goods often requires significant distances to be covered, leading to significant emissions.

Shipment waste is a significant contributor to greenhouse gas (GHG) emissions in the private commerce sector, especially carbon dioxide (CO_2) emissions. According to data from 2018, transportation of both passengers and freight accounted for 28% of GHG emissions globally.

A reduction in shipment waste can be achieved by implementing various practices that can be addressed by AI, increasing fuel efficiency, optimizing vehicle capacity utilization and improving scheduling.

1. Fuel Efficiency: Logistic Service Providers (LSPs) can improve fuel efficiency by adopting more fuel-efficient vehicles, optimizing routes [31] and reducing idling times. This not only reduces emissions but also saves costs.
2. Optimal Vehicle Capacity Utilization: By ensuring that vehicles are fully loaded and operate at maximum capacity, LSPs can reduce the number of trips required to transport goods, thereby reducing emissions and fuel consumption.
3. Scheduling: LSPs can also improve sustainability by carefully scheduling deliveries and reducing the amount of time vehicles spend on the road. This can be achieved through better route planning and scheduling, which reduces unnecessary travel time and emissions.

Dmitri Fedorchenko, CEO and co-founder of Doft, an online freight shipping marketplace, states in an article for Forbes that: "The number one way AI can optimize resources in trucking and shipment is by optimizing backhauls. Thirty-five percent of all miles are driven by unloaded trucks. An empty truck not performing its primary function is a complete waste of fuel".

Moreover, logistics activities generate a large amount of data that can be both structured, such as data stored in databases and unstructured, such as data contained in emails, invoices and other documents.

This amount of data can be leveraged by artificial intelligence (AI) to improve logistics efficiency and effectiveness and providing valuable insights that can be used to optimize logistics processes, helping in making data driven decisions and reducing costs.

Regarding the first cluster for the application of AI in Smart Logistics, "Strategic and tactical process optimization", many articles focused on the optimal location of warehouses to increase efficiency in deliveries and cut costs and emissions.

Moreover, many AI techniques have been used to solve for the ideal structure of reverse logistics infrastructure in both small and large-scale settings [43].

Reverse logistics is a term which refers to the process of returning goods, products or materials from the end customer to the manufacturer for the purpose of recovery, reuse, disposal or resale to ensure an efficient use of resources and to reduce waste. In the realm of Reverse Logistics, other key application of AI emerged from literature, in [43] the authors stated that AI can help mitigate the unpredictability in warehousing by forecasting returns and enhancing decision-making for inventory management.

Moreover, AI applications are capable of carrying out multiple sorting and inspection tasks, helping in determining if retuned products meet the standards to be collected. Cobots (Collaborative Robots), equipped with machine learning capabilities, are becoming widely used in warehouses to help humans in tasks such as pattern recognition, diagnosing failures, part identification and even interpretation of results from testing equipment.

Apart from Reverse Logistics, the integration of digital technologies and applications into logistics operations in the Fast-Moving Consumer Goods (FMCG) industry and in transport service providers has made a significant impact on sustainability. The economic benefits of digitization are paramount in reducing logistics costs, improving delivery times, reducing delays, optimizing inventory management, enhancing reliability and increasing flexibility [23]. The sustainability impact of digitization in logistics is especially pronounced when considering the economic implications, with this aspect deemed more important than other dimensions, but the implications on the other pillars of sustainability are gaining more and more interest over the years. Moreover, in the logistic sector many benefits are difficult to classify into one of the 3 pillars of sustainability, as a reduction in resources used usually means a reduction in waste and pollution.

The adoption of AI in logistics has brought numerous benefits that have not only improved the efficiency and effectiveness of operations but also positively impacted the sustainability of the industry. Here, we will explore the most immediate benefits of AI in logistics and their implications for sustainability.

One of the most immediate benefits of AI in logistics is the optimization of vehicle routing. AI algorithms can analyze data such as traffic patterns, road conditions and delivery schedules to optimize the routing of vehicles. This not only reduces fuel consumption and decreases the time needed for deliveries and material handling operations but also reduces the wear and tear of equipment.

AI can also improve the utilization and saturation of trucks by maximizing their payload. By optimizing the utilization of trucks and vehicles, companies can reduce the number of trips needed to deliver goods, thereby reducing costs and emissions. Reducing the number of trips or trucks required to deliver the same amount of goods, companies can reduce costs, emissions and traffic congestion, leading to an improvement of their environmental sustainability performance.

In addition, AI can adapt to changing conditions in real-time, adjusting the priority of individual deliveries or changing routes according to traffic data. This improves the timeliness of deliveries, enhancing customer satisfaction and can lead to a better economic performance.

AI can also be used to identify and monitor potential risks or causes of hazard, thereby improving the social aspects of sustainability. For instance, computer vision algorithms can be used to recognize obstacles on the road or inside a plant, preventing injuries and car accidents due to human errors or distractions. According to reports, autonomous technology can reduce traffic accidents by 87%.

Predictive maintenance is another benefit of AI in logistics. AI algorithms can analyze data from sensors on trucks and equipment to predict potential equipment failures before they occur. Thanks to the anticipation of equipment failures, companies can avoid dangerous situations for their operators, reduce injuries, reduce costs for breakdowns improving the safety of their operators and their social sustainability performance.

Also data from warehouse or material handling activities can be leveraged by AI to optimize several aspects of company operations. By improving the facility design, companies can reduce costs and time for material transportation. By reducing out-of-stock, thanks to an improved forecasting of demand, companies can increase revenues. Optimizing inventory levels, thanks to better monitoring of goods in the warehouse, helps to cut costs and reduce waste due to the obsolescence of products. Lastly, an optimized and more efficient usage of lighting and cooling inside the facilities will greatly reduce the energy consumption of the companies, thereby improving their sustainability performance.

Table 1 and **Table 2** present a list of benefits associated with the implementation of AI solutions in logistics, which were identified through the review of the literature in sections 2.1.1 and 2.1.2. The benefits are divided based on their nature, with some being classified as tangible benefits, while others are classified as intangible benefits.

Tangible benefits refer to those benefits that can be measured in quantifiable terms, such as cost savings, increased efficiency and improved accuracy. Intangible benefits, on the other hand, refer to benefits that are difficult to quantify, such as improved customer satisfaction, improved image, better quality of life and improved attractiveness to shareholders.

By presenting the benefits in this manner, giving a comprehensive overview of the potential advantages of implementing AI solutions in logistics also highlights the fact that some benefits may be more difficult to measure than others. This provides further insights into the potential return on investment, as well as the non-monetary benefits that can be realized through the use of these technologies.

Table 1: Tangible benefits of AI application towards sustainability in logistic companies

Tangible Benefits	
Benefit	**Description**
Material reduction [31][3]	AI allows inventory optimization and therefore a reduction in waste due to obsolescence.
Energy consumption reduction [31][3]	By optimizing routing, reducing empty runs, optimizing lighting and cooling etc.
Waste disposal costs reduction [31]	A reduction in waste generated by the company, leads to less costs for its disposal.
More efficient routing [31]	AI allows the optimization of the routes for transportation reducing costs and time.
Future cost reduction for loss of welfare due to environmental issues [33]	The sustainability improvements AI brought, can help reduce the environmental impact of logistics operations and their future financial impact on the company.
Reduction in costs for traffic congestion [36] [33] [29]	Strictly linked with a more efficient routing. Less time spent in traffic leads to less fuel used, less time to perform operations and a reduction in emissions.
Better access to certain markets (regulatory compliance) [3]	Certain markets may ask sustainability standards to be able to enter, AI can help achieve those standards while improving efficiency.
Lower liability costs (if expected from regulations) [3]	An improved sustainability performance may lead to less liabilities, if expected from regulation to penalize not responsible practices

Table 2: Intangible benefits of AI application towards sustainability in logistic companies

Intangible Benefits	
Benefit	**Description**
Improved image [31]	An improvement in sustainability may lead to a better Brand Image to the eyes of Stakeholders and Shareholders.
Improved attractiveness to stakeholders and shareholders [31] [3]	Stakeholders are increasingly interested in sustainability, improved sustainability performances thanks to AI will attract them
Increased motivation of stakeholders towards sustainability issues [31]	The improvements in sustainability performances may interest stakeholders who new to sustainability topics.
Reduction of emissions and better quality of life [33]	A reduction in air pollution leads to health improvements and a better quality of life for the community
Push towards integration along the Supply Chain [31]	AI can produce its biggest benefits when it has visibility and data of the overall supply chain. To fully leverage its potential, an integration along the supply chain is necessary

2.2. Measuring sustainability

In order to gain a more comprehensive understanding of the extent to which existing methods could be applied to assess the sustainability implications of AI solutions in logistics, a literature review was conducted. The review focused on identifying and examining existing studies on the assessment and evaluation of logistics and transportation, with a particular emphasis on those that explored the sustainability implications of these activities.

The review aimed to identify any existing methods or frameworks that could be adapted to evaluate the sustainability implications of AI solutions in logistics, as well as to identify any gaps or limitations in the existing literature.

The study conducted by Melacini et al. [31] highlights the limited amount of literature that specifically examines environmental sustainability, from the perspective of companies engaged in logistics and transportation activities. The study shows that there is a growing focus on distribution and sustainable transportation activities, with attention being paid to both technological innovation and management strategies. However, there is a lack of research on other functions involving logistics, such as warehousing and inventory management.

Accordingly, it was found that there is little literature available on the assessment and evaluation of logistics and transportation sustainability. The existing literature primarily focuses on transportation and routing, with limited research on other functions within logistics, such as warehousing and inventorying. This highlights the need for further research in these areas to understand the potential impact of sustainability-focused solutions and to develop effective evaluation methods.

In the following chapter, a review of the Key Performance Indicators (KPIs) found in literature, that could be applied to the topic of evaluating the sustainability implications of AI solutions in logistics, is presented.

2.2.1. KPIs for sustainability in logistics

KPIs are measurable values that indicate how well an organization, or a system is achieving its objectives. They are used as a tool to measure the performance of an organization against its goals, targets or objectives and can be used to track progress over time, to identify areas that need improvement and to ensure that resources are being allocated efficiently.

They are useful because they provide a common language and set of metrics for organizations and stakeholders to measure and evaluate the effectiveness of operations.

Authors in [36] underline how choosing a sustainable transportation indicator is not a neutral process as it reflects the choice of a particular level of analysis, such as geographical, sectoral, or temporal and can be constrained by data availability. Therefore, it is important to understand the underlying assumptions and perspectives used to select and define these indicators. Figure 4 illustrates how the choice of ratios and reference units can reflect different levels of analysis in transport and influence the interpretation of results.

Indicators	Level of analysis
Transport Intensity tonne-kms / total output Modal Split road tonne-kms / total tonne-kms Vehicle Utilisation vehicle-kms / tonne-kms Energy Efficiency energy consumed / vehicle-km	- logistics infrastructure - supply networks - scheduling of flows - managing transport resources - vehicle operation - vehicle design

Figure 4: Different levels of analysis depending on the choice of indicators [36]

Absolute indicators such as Health, Community Livability, or Work Equity are often proposed from a community perspective as important aspects of sustainability. However, measuring these indicators in a standard way is difficult due to the multiple perspectives and factors that underlie them. Therefore, for the purpose of this research, the focus was on exploring KPIs that could be used from a company perspective, which are typically more tangible and easier to measure. This approach allows for a more focused and manageable set of indicators to be evaluated, which can provide practical insights for companies seeking to assess the sustainability of their logistics operations.

In the following sections, the main KPIs to evaluate sustainability in logistics are presented. For each KPI the formula, a brief description and how can AI improve that indicator, is reported.

Fuel Used

$$\text{Fuel Used} = \text{Liters or Gallons of fuel used} \quad (1)$$

The amount of fuel used calculated as the mere liters or gallons used by logistics operation (1), can be a relevant sustainability indicator in logistics, as it directly relates to greenhouse gas emissions and air pollution. By reducing the amount of fuel used in logistics operations, companies can lower their carbon footprint and contribute to mitigating climate change.

AI can improve fuel usage in logistics operations by optimizing routing and reducing empty miles, which can significantly decrease the amount of fuel consumed. AI can also provide real-time data on traffic, weather and other factors that affect fuel efficiency, allowing companies to make more informed decisions about their logistics operations. Furthermore, AI can analyze historical data to identify patterns and trends in fuel usage, which can help companies develop more effective strategies for reducing fuel consumption over time.

Energy Consumption per Ton/Km

$$\text{Energy Consumption per}\,\frac{\text{Ton}}{\text{Km}} = \frac{\text{KWh}}{(\text{Weight} \times \text{Km})} \quad (2)$$

Calculated as in (2), it measures the energy efficiency of transportation per unit of weight and distance. It takes into account both the weight of the cargo and the distance traveled, which are two important factors that contribute to energy consumption and greenhouse gas emissions in logistics. This indicator can be used to track the energy efficiency of different transportation modes or vehicles, as well as to compare the efficiency of different transportation routes or supply chain configurations.

AI can improve the performance of this sustainability indicator by optimizing the routing and scheduling of transportation operations. Similarly to the previous indicator, AI algorithms can identify the most efficient routes and schedules for transportation, which can result in a reduction in energy consumption and an improvement in energy efficiency.

Moreover, as described more specifically for the next indicators, AI can also optimize vehicle loads and reduce empty miles, thus increasing the amount of goods transported per unit of energy consumed.

Energy efficiency: Distance/Energy consumed

$$\text{Energy efficiency: Distance/Energy} = \frac{\text{Km}}{\text{KWh}} \quad (3)$$

Calculated as in (3), this KPI measures the distance traveled per unit of energy consumed and it can be used to compare the energy efficiency of different transportation modes, vehicles, or routes. A higher value of Km/KWh indicates a more energy-efficient transportation process, which can result in lower greenhouse gas emissions and lower fuel costs.

Similarly to the previous indicators, AI can play a significant role in improving the performance of this KPI. Analyzing various factors such as traffic congestion, weather conditions and delivery schedules to identify the most efficient route for a given shipment. But also optimizing the use of energy resources, such as fuel or electricity. This can reduce unnecessary energy consumption, leading to a lower Km/KWh ratio.

In addition, AI can be used to analyze data from sensors installed in vehicles and logistics facilities to identify areas where energy efficiency can be improved, such as inefficient driving behaviors or equipment with higher energy consumption and provide recommendations to reduce energy waste and improve the overall sustainability performance of the logistics operation.

Weight Based Vehicle Utilization

$$\text{Weight Based Vehicle Utilization} = \frac{\text{Actual Payload}}{\text{Maximum Payload}} \quad (4)$$

Calculated as in (4), this ratio measures the efficiency of the transportation by comparing the actual weight of goods carried to the maximum weight that the vehicle is designed to carry. This metric is particularly important in reducing the number of trips required to transport a given amount of goods, thereby reducing the energy consumption and emissions associated with transportation.

Using predictive analytics and machine learning algorithms, AI can optimize vehicle utilization by predicting demand and matching the right vehicles to the right loads. Leading to a reduction in empty miles and an increase in the amount of cargo being transported per vehicle, minimizing the number of vehicles required to transport it.

Volume Based Vehicle Utilization

$$\text{Volume Based Vehicle Utilization} = \frac{\text{Actual Volume of Goods}}{\text{Maximum Volume}} \quad (5)$$

Analogously as in (4) using Volume Based Vehicle Utilization (5) as a sustainability indicator in logistics can be useful in ensuring efficient use of transport capacity and reducing waste. However, it may not be appropriate for all types of cargo, as some products may have weight limitations rather than volume limitations.

Similarly to (4), using AI algorithms to analyze data on the size, weight and shape of goods and the available space in the vehicle, it is possible to determine the most efficient way to load the goods to maximize the use of the available space, maximize the use of transport capacity and minimize empty or partial loads. This will lead to an increase in the actual volume transported, which will result in a reduction in the number of trips needed to transport the same amount of goods and a decrease in fuel consumption and emissions.

Percentage of Empty Running Time

$$\text{Percentage of Empty Running Time} = \frac{\text{Empty Running Time}}{\text{Total Running Time}} \times 100 \quad (6)$$

Calculated as in (6), it provides a measure of the efficiency of logistics and transportation operations. The higher the percentage of empty running time, the lower the efficiency of the transportation operation, as it means that vehicles are traveling without carrying any load. This results in wasted fuel, increased emissions and higher transportation costs. Hence, by reducing this KPI, companies can improve their sustainability performance while also increasing the utilization of their assets.

As already mentioned for previous KPIs, AI can have a huge impact on the performances this indicator, optimizing routes and scheduling and, most importantly, reducing the impact of backhauls, allowing companies to collaborate more effectively and to share available capacity with other shippers and carriers, reducing the number and the amount of resources wasted on empty trips.

Percentage of Vehicle Meeting Emission Standards

$$\text{Percentage of Vehicles Meeting Emission Standards} = \frac{\text{Vehicles Meeting Standards}}{\text{Total Fleet}} \times 100 \quad (7)$$

The KPI in (7) can help companies assess their environmental impact and compliance with regulations related to emissions. This indicator is particularly important in urban areas where high levels of pollution from vehicles can have significant health and environmental impacts. However, the effectiveness of this indicator may be limited by variations in emission standards across different regions and countries.

By using AI algorithms to analyze data on vehicle usage and emission levels, companies can identify the most efficient and effective ways to deploy their vehicles to reduce emissions. For example, AI can monitor the emissions of their vehicles in real-time and provide alerts if any vehicles are not meeting emission standards. This can allow companies to take immediate action to correct any issues, ensure that their vehicles are operating at peak efficiency and identify which vehicles in a fleet should be replaced with newer, more fuel-efficient models to further reduce emissions.

Average age of the fleet

$$\text{Average age of the fleet} = \frac{\sum \text{Age of the Vehicle}}{\text{Total Fleet}} \quad (8)$$

The KPI in (8) provides information about the potential environmental impact of vehicles. Older vehicles tend to have higher emissions and lower fuel efficiency, which can contribute to negative environmental effects. By tracking the average age of the fleet, companies can set goals to replace older vehicles with newer, more efficient ones, which can reduce their environmental footprint.

AI can help improve the performance of this sustainability indicator by optimizing fleet replacement decisions. Analyzing data on vehicle usage, maintenance, fuel consumption and emissions, AI can determine which vehicles to replace. Moreover, AI could assist in the selection of new vehicles for the fleet suggesting, based on vehicle characteristics, the ones that have lower environmental impact and higher fuel efficiency.

Modal Split

$$\text{Modal Split} = \frac{\text{Distance of Each Mode}}{\text{Total Distance Travelled}} \quad \forall\, transportation\, mode \quad (9)$$

Modal Split (9) is a commonly used indicator in the transportation and logistics sector to evaluate the distribution of different transportation modes used to transport goods. It allows for an understanding of the relative importance of different modes of transport for logistics activities, as well as the potential to shift towards more sustainable ones.

The usage of AI may lead to several improvements by optimizing the choice of transport mode for each shipment based on factors such as distance, volume, weight and delivery time requirements, to determine the most efficient and sustainable transport mode for each shipment.

Reliability

$$\text{Reliability} = e^{-\frac{t}{MTTF}} \quad (10)$$

Reliability, calculated as in (10), affects the efficiency and effectiveness of the transportation system, which in turn impacts social, economic and environmental dimensions. A reliable transportation system can reduce delivery times and costs, enhance customer satisfaction thus reducing emissions and improving the environmental performances of the companies. However, measuring reliability can be complex, as it may require detailed data collection and analysis. Moreover, a high level of reliability may sometimes lead to overcapacity and excess resources being employed, which could undermine sustainability in terms of economic and environmental impacts.

Predictive maintenance, a field of application of AI, can reduce the risk of unexpected breakdowns and keep vehicles in optimal condition, improving reliability, reducing the need for last-minute repairs and replacements that can be costly and inefficient.

Amount of injuries

$$\text{Amount of injuries} = Number\ of\ Injuries \quad (11)$$

Using the Number of Injuries (11) as a sustainability indicator can provide information about the safety of transportation operations and the social pillar of sustainability. This KPI as seen for "Percentage of Vehicle Meeting Emission Standards" in (7) may be affected by local regulations and different definitions of injury among different companies and countries.

Providing real-time monitoring and analysis of the working conditions and activities of the workers, AI can identify potential safety hazards and provide alerts to prevent accidents from happening. For example, AI can analyze video footage of workers operating heavy machinery and detect any unsafe behavior or potential hazards, decreasing the number of injuries of the operators.

Physical Load

$$\text{Physical Load} = Kgs\ carried\ per\ employee \quad (12)$$

Applying the Kg carried per employee (12) as a sustainability indicator can be a double-edged sword, this indicator may imply that a higher Kg carried per employee value indicates a more efficient and sustainable logistics operation. However, a higher Physical load per employee will inevitably increase the number of injuries for the operators, decreasing the social sustainability performances of the companies and implying additional costs for the company.

Thanks to the recent application of AI to Cobots and Robots for picking, human operators can be replaced by machine-pickers, which will drastically reduce the amount of weight carried, resulting in less injuries.

Use of daylight

$$\text{Use of daylight} = \frac{Time\ Using\ Artificial\ Lighting}{Total\ Time} \times 100 \quad (13)$$

The Percentage of use of daylight (13) can be used as a sustainability indicator from an energy consumption perspective. It could be used to track the usage of lighting in warehouses, loading docks and other logistics facilities to identify areas where energy efficiency improvements could be made.

AI solutions can analyze data on lighting usage, such as the time of day, the type of lighting used and the duration of use and leverage this information to develop optimized lighting schedules. For instance, AI can determine the optimal time for turning on and off lights based on the level of activity in the logistics facility, helping to reduce the amount of time that artificial lighting is used, reducing energy consumption and carbon emissions.

Percentage of Renewable Energy

$$\text{Percentage of Renewable Energy} = \frac{KWh\ from\ Renewables}{Total\ KWh\ used} \times 100 \quad (14)$$

Calculated as in (14), the Percentage of energy measures the proportion of energy consumed by logistics operations that is generated from renewable sources such as solar, wind, or hydro power. This indicator is useful in tracking progress towards a more sustainable energy mix and reducing the carbon footprint of logistics operations. It is also a way for companies to demonstrate their commitment to sustainability to stakeholders and customers. As in previous KPIs, the results in this indicator may be deeply impacted by the location of the company, as renewables may not be available everywhere.

Several improvements can be brought by the usage of AI algorithms, which can be used to predict energy demand and optimize the use of renewable energy sources to meet that demand.

Additionally, AI can improve the performance of this indicator by helping logistics companies make strategic decisions about renewable energy investments, to identify the most cost-effective renewable energy sources and investment opportunities.

Temperature

$$\text{Temperature} = Temperature\ °C/F \quad (15)$$

The temperature of logistics facilities (15) can affect the energy consumption of heating, ventilation and air conditioning systems, which can have a significant impact on the environment.

Adjusting temperature settings and ventilation systems as needed to maintain the desired temperature range while minimizing energy use, AI can help reduce energy costs and lower greenhouse gas emissions, while also ensuring the safety and quality of the products being transported and stored.

Average Distance between Aisles

$$\text{Average Distance between Aisles} = \frac{\sum Distance\ between\ Aisles}{Number\ of\ Aisles} \quad (16)$$

Average Distance between Aisles (16) can have an impact on energy consumption and efficiency inside plants. Wider aisle can result in a lower storage density, higher land consumption and more importantly higher fuel consumption by material handling systems during daily operations.

This is a popular area of application for AI algorithms, which can determine the optimal aisle width and configuration that maximizes space utilization while minimizing energy consumption and travel time. AI can also help companies monitor and adjust the aisle width and layout over time, based on changes in demand and product mix.

Inventory Accuracy

$$\text{Inventory Accuray} = \frac{Number\ of\ inventory\ errors}{Number\ of\ inventoried\ items} \times 100 \quad (17)$$

Inventory Accuracy, calculated as in (17), can help to reduce waste, improve resource efficiency and prevent unnecessary inventory carrying costs.

By ensuring that the inventory records are accurate, companies can reduce the likelihood of overstocking or stockouts, which can result in unnecessary transportation, storage and disposal costs. It can also help to improve supply chain transparency and reduce the risk of errors or inaccuracies that can lead to operational inefficiencies.

Thanks to AI, companies can have real-time visibility into inventory levels and predict demand for products, enabling companies to better manage their inventory and reduce waste. Moreover, thanks to image recognition, AI can also help to identify potential errors and inconsistencies in inventory data, alerting companies to take corrective actions before they result in costly errors or environmental waste.

Amount of waste

$$\text{Amount of waste} = Pieces, Volume, Weight\ or\ Value\ of\ Waste \quad (18)$$

Strictly connected with many of the previous indicators, the amount of waste (18) is a very common indicator of the sustainability performance of a company as it reflects the efficiency of the system in terms of resource use. Measuring the amount of waste generated during transportation, storage and distribution activities can help companies to identify opportunities to reduce waste and its disposal costs and optimize resource utilization.

Thanks to the optimization of inventory levels, AI can help reduce the amount of waste due to overproduction or underutilized inventory. Moreover, it can help identify areas of inefficiencies along the supply chain and take corrective actions.

To summarize sustainability performance evaluation of AI solutions in logistics is an area that lacks literature. However, traditional KPIs used to measure logistics sustainability can be applied to AI solutions. These KPIs can be monitored to determine the effectiveness of the solutions in improving the sustainability performance of companies.

However, these KPIs may not account for the negative impacts of AI solutions on sustainability, such as the amount of power needed to run the algorithms. It is important to consider the full life cycle of AI solutions and their environmental impact, from the manufacturing of hardware to energy consumption during operation. Thus, while traditional KPIs can be useful in evaluating the sustainability performance of AI solutions, they may not provide a complete picture of the impact of these solutions on sustainability.

In the following tables are reported 2 different classifications of the KPIs just described, in **Table 3** and **Table 4**, a classification per possible applications in different logistics function is proposed. In **Table 5** and **Table 6** the KPIs are classified based on the dimensions that can be improved by their application to logistics operations.

	Formula	Delivery Routing	MHS	Picking	Inventorying	Inbound Logistics	Warehouse management
Fuel Used	Liters or Gallons of fuel	x	x				
Energy Consumption per ton-km	$\frac{\text{KWh}}{(\text{Weight} \times \text{Km})}$	x	x				
Energy efficiency: distance/energy consumed	$\frac{\text{Km}}{\text{KWh}}$	x	x				
Weight Based vehicle utilization	$\frac{\text{Actual Payload}}{\text{Maximum Payload}}$	x	x				
Volume Based Vehicle Utilization	$\frac{\text{Actual Volume of Goods}}{\text{Maximum Volume}}$	x	x				
% of empty running time	$\frac{\text{Empty Running Time}}{\text{Total Running Time}}$	x	x				
Proportion of vehicle fleet meeting emission standards	$\frac{\text{Vehicles Meeting Standards}}{\text{Total Fleet}}$		x				
Average age of the fleet	$\frac{\sum \text{Age of the Vehicle}}{\text{Total Fleet}}$		x				
Modal Split	$\frac{\text{Distance of Each Mode}}{\text{Total Distance Travelled}}$	x	x				
Reliability	$e^{-\frac{t}{MTTF}}$		x				

Table 3: Transportation KPIs, classification per applicability

	Formula	Delivery Routing	MHS	Picking	Inventorying	Inbound Logistics	Warehouse management
Amount of injuries	$Number\ of\ Injuries$			x			
Physical Load	$Kgs\ carried\ per\ employee$			x			
Use of daylight	$\frac{Time\ Using\ Artificial\ Lighting}{Total\ Time}$						x
Percentage of renewable energy	$\frac{KWh\ from\ Renewables}{Total\ KWh\ used}$		x				x
Temperature	$Temperature\ °C/F$						x
Average distance between aisles	$\frac{\sum Distance\ between\ Aisles}{Number\ of\ Aisles}$		x	x			x
Inventory Accuray	$\frac{Number\ of\ inventory\ errors}{Number\ of\ inventoried\ items}$				x		
Amount of waste	$Amount\ of\ Waste$				x	x	

Table 4: Other Sustainability KPIs, classification per applicability

	Cost	Time	Quality	Flexibility
Fuel Used	x			
Energy Consumption per ton-km	x			
Energy efficiency: distance/energy consumed	x			
Weight Based vehicle utilization	x			
Volume Based Vehicle Utilization	x			
% of empty running time	x	x		
Percentage of vehicle fleet meeting emission standards	x	x		
Average age of the fleet	x			
Modal Split	x	x		x
Reliability	x	x		

Table 5: Transportation KPIs, classification per dimension of analysis

	Cost	Time	Quality	Flexibility
Amount of injuries	x			
Physical Load	x			
Use of daylight	x			
Percentage of renewable energy	x			
Temperature	x			
Average distance between aisles	x	x		
Inventory Accuray	x	x	x	x
Amount of waste	x		x	x

Table 6: Other Sustainability KPIs, classification per dimension of analysis

2.3. Algorithms

From the review of scientific literature, different AI algorithms have been applied to solve logistics problems, with different performances. This is due to the complexity of the problems, the quality of the data used for training and the specific design of the algorithm. The following chapter will give an overview of the most common ones and their applications on logistics problems.

2.3.1. Reinforcement Learning

Reinforcement learning (RL) is a type of machine learning that enables an agent to learn from experience and determine the best course of action to maximize a reward and interact with, rather than depend on, their environment [21].

More specifically, it is a process where a learning agent receives evaluative feedback in the form of rewards for its actions. It is based on the concept of learning over time through a trial-and-error approach: the agent tries different actions in various situations, evaluating their immediate and long-term effects on the environment and their overall contribution to the agent's goals.

RL can be broken down into five core components: environment, agent, state, action and reward.

1. The environment refers to everything external to the learning agent in the RL problem.
2. The agent is the learning entity, which maps states to actions by trying different actions and engaging with the environment.
3. The state is the agent's interpretation or summary of a particular situation or arrangement of the environment as perceived by the agent.
4. An action is a mechanism that modifies some characteristic or aspect of the environment, potentially resulting in a new state.
5. The reward, an external signal which serves as a means of conveying the objective of the RL problem to the agent, which seeks to choose the actions that maximize its cumulative reward over time.

One of the advantages of RL it's the ability to respond to dynamic environments, using the trained model in a new environment [21]. Thanks to its applicability and the wide range of applications in various disciplines where training the agent on all possible examples is challenging, RL has gained popularity in recent years.

From a review of the literature, consistently with what mentioned before, RL has been applied with success to different logistics problems, mainly focusing on routing.

Starting from the simple Vehicle Routing Problem, described in 2.1, RL has been applied in [22] to the routing of logistics vehicles with a specific capacity (Capacitated Vehicle Routing Problem, CVRP) for multiple distribution centers. The algorithm had strong efficiency in terms of solution accuracy and solution time in the routing length and time. From the results obtained emerges how the reinforcement learning method is very effective for solving the CVRP problem and can effectively solve the logistics distribution problem and reduce logistics transportation costs.

Increasing the complexity of the problem and the number of constraints, such as the opening times of customers or the timespan in which a workstation needs materials to perform its operations; the literature focused on the Vehicle Routing Problem with Time Windows (VRPTW) and Pickup and Delivery Problem with Time Windows (PDPTW).

The authors in [19] utilized Reinforcement Learning (RL) on two simulated factory layouts to optimize the delivery of parts from the warehouse to the workstations. The results showed that RL effectively decreased the Material Handling (MH) costs in a variety of initial plans. The minimum cost reduction achieved in both layouts was 54.7%, while the average cost reduction was 82.8%.

[21] employed Reinforcement Learning (RL) to improve material handling operations in a factory setting. The company faced challenges in managing the dynamic demands of order variations, interruptions, resource traffic and production line work progress. RL was able to minimize the time, distance and energy consumed in material handling tasks, making it easier to respond to individual needs in real-time and increasing the overall responsiveness of the production line. Hence the implementation of RL can contribute to better decision making, routing and coordination of AGVs with changing load and unload stations in the material handling process.

Another application of Reinforcement Learning found in [46]. The scarcity of workers in the logistics sector has driven the use of robots for picking and depalletizing tasks. However, robots have not been as effective as humans due to the varied nature of objects they handle. To address this issue, the authors applied deep reinforcement learning to train the robot in trajectory control during the process of picking up a target object from a box. The results showed that the proposed method outperformed the conventional methods in terms of learning performance. Additionally, the proposed method also demonstrated high performance when applied to a different object that was not used during the learning process. These results indicate that RL can effectively improve the performance of robots in picking tasks in a warehouse environment.

2.3.2. Ant Colony Optimization

Ant Colony Optimization (ACO) is a probabilistic meta-heuristic technique in the field of swarm intelligence that studies the behavior patterns of social insects like ants, bees and termites. The algorithm simulates the behavior of ants in finding the optimal path between the ant colony and a food source.

The ACO also incorporates the abilities of ants to remember past actions and knowledge about the distance to other locations. Communication between ants is achieved through the use of pheromones. As ants travel, they deposit a constant amount of pheromones, which other ants follow. The more the ants travel a particular path, the more attractive the path becomes to subsequent ants. Over time, the shortest routes receive the most pheromones and attract the majority of insects, leading to the discovery of the optimal path.

The ACO algorithm follows a specific set of steps, which include:

1. Initializing the number of ants and pheromones;
2. Determining the next target node by roulette;
3. Updating pheromones on the path after each round;
4. Iterating the process until the optimal path is found.

The algorithm has been applied to various fields, including the traveling salesman problem and is known for its robustness and automatic search process. However, ACO also has limitations such as slow convergence, susceptibility to local convergence and extensive calculations [20].

In the context of the traveling salesman problem (TSP), an individual ant acts as a vehicle and its route is constructed by incrementally visiting customers until all customers have been covered. The ant starts at the depot, selects customers from a list of feasible locations, updates the storage capacity of the vehicle and returns to the depot when the capacity constraint is met, or all customers are visited.

A real-world application of ACO to the Travelling Salesman Problem is found in [11]. In this paper the authors apply Ant Colony Optimization to the context of manual picking by workers in a warehouse. The minimization of the travel distance of pickers can be approached as a TSP, where the picking locations listed in the picking list reflect the cities to be visited. Picking is generally recognized as a very expensive activity because it tends to be either very labor intensive or capital intensive and since pickers spend approximately 50% of the time travelling. Ant Colony Optimization returns the optimal length of the picking tour in 88.89% of results.

Moreover, the performance of the ACO algorithm is particularly appreciable for complex warehouse configurations, where the shortest path generated is significantly better than that returned by other routing algorithms. In this paper the algorithm was also applied to a real case study and it was able to reduce by 33% the travel time of manual pickers.

Thanks to its versatility, ACO has been applied, in different forms, also to the other logistics problems which involve the finding of the best route possible.

The application of the algorithm to solve VRP is explored by the authors of [4], in which they applied Ant Colony optimization to solve a combination of location inventory problem, location routing problem and the inventory routing problem. By utilizing data from an open-source dataset, it simulates a scenario where the Ant Colony Optimization (ACO) algorithm is employed to find the optimal path for location-based inventory delivery. Compared to static algorithms, ACO can find sub-optimal routes in dynamic routing.

ACO's ability to adapt to changing conditions and take corrective action makes it well-suited for solving problems in dynamic environments such as online retail delivery. However, the computational power required to apply the algorithm in real-life scenarios increases very rapidly.

Other attempts of applying the Ant Colony Optimization (ACO) method have been made in [6] and [20]. The first study compares the ability of the single ant colony and multiple ant colony methodologies in finding solutions to the Vehicle Routing Problem (VRP) for problems with varying numbers of customers.

The study found that the Ant Colony Optimization (ACO) method can produce results within 1% of the known optimum for small problems. However, it is not as efficient in solving larger problems, consistent with previous research. Multiple ant colonies show improvements on larger problems, but for smaller problems, they produce results comparable to traditional methods while requiring more computational power.

The second study implements an improved version of the Ant Colony Optimization (ACO) algorithm on a simulated warehouse layout. The improved ACO is a combination of the standard ACO and the Particle Swarm Optimization (PSO) algorithm. The results show that the improved ACO algorithm finds a shorter path, reducing the length of the path within the warehouse.

While the basic algorithm is appropriate for vehicle routing, the improved ACO reduces the distance found by the standard one by 20%.

More specific papers also explore multi modal ways of transportation. As an example, [10] proposes a mechanism for combining Unmanned Aerial Vehicles (UAVs), also known as drones, with delivery trucks for parcel delivery logistics. The trucks serve as mobile launching and retrieval sites for the drones, allowing for efficient use of the drones' capabilities. The problem is formulated as a VRPTW, characterized by a multi-objective optimization model with two conflicting objectives: minimizing travel costs and maximizing customer service level in terms of timely deliveries. The solution to this problem is obtained through a Collaborative Pareto Ant Colony Optimization algorithm and is compared against Non-dominated Sorting Genetic Algorithm II (NSGA-II). The model was evaluated using a benchmark dataset and the results showed that the Collaborative P-ACO algorithm was able to provide better solutions in terms of both travel distance and customer satisfaction compared to NSGA-II.

2.3.3. Hill Climbing Algorithm

Hill Climbing is a simple optimization algorithm that can be applied to a variety of mathematical optimization problems. The idea behind the algorithm is to find the highest point in a given problem space by continuously moving in the direction of the highest value or elevation. This movement is made by selecting the best local neighbor, which is the state that results in the greatest increase in the value or elevation of the current state. The algorithm terminates when the highest value is reached and no further improvement can be made.

One of the most well-known applications of Hill Climbing is to further optimize the Traveling Salesman Problem, where the objective is to minimize the total distance traveled by a salesman visiting multiple cities.

It's important to note that Hill Climbing can get stuck in a local optimum, meaning a high point in the problem space that is not the global optimum. This is because the algorithm only considers the best local neighbor and does not look beyond that. To overcome this limitation, other optimization algorithms such as Genetic Algorithms can be used.

2.3.4. Evolutionary Algorithms

Evolutionary Algorithms (EAs) are a type of heuristic search methods that are based on the concept of Darwinian evolution. These algorithms have strong attributes, including robustness and flexibility, which make them ideal for solving complex optimization problems and finding global solutions. EAs have a high probability of finding a near-optimal solution in the early stages of the optimization process and do not require any fitness gradient information. They are easy to process in parallel and have the ability to escape from local optimum, which can be a problem for deterministic optimization methods.

EAs are particularly effective in solving multi-objective optimization problems, as they can handle a range of design variables, including integer, discontinuous and discrete variables. They are not sensitive to the shape of the Pareto front and the cost grows linearly with the complexity of the problem.

Many algorithms fall under the umbrella of EAs, among the other two popular methods applied to logistics problems are Genetic Algorithms and Particle Swarm Optimization.

2.3.4.1. Genetic Algorithms

The genetic algorithm (GA) approach to optimization is based on the idea of natural selection. Like other evolutionary algorithms, it mimics the process of evolution, where the strongest elements are reinforced while the weaker elements are eliminated.

The GA method uses strings of integers known as chromosomes to represent the parameters being optimized in a stochastic search of the solution space, each integer within the chromosomes is known as a gene. An initial population of chromosomes is generated at random and is then decoded to obtain the parameters to be introduced into the system model. A simulation is run, and results are obtained, the cost values are sorted and the best chromosomes are chosen based on the lowest cost values.

The best chromosomes are then subjected to reproduction, crossover and mutation processes.

1. The reproduction process involves keeping the best chromosomes for the next population, while the others are replaced by new chromosomes generated through crossover and mutation.
2. Crossover involves exchanging genes between two parent chromosomes to create two offspring.
3. Mutation randomly selects and alters the values of certain genes to provide a random element in the GA search process.

On simpler problems, as seen in [10], Gas may perform worse than other algorithms such as Ant Colony Optimization which are specifically designed for those types of problems. However, as the complexity of the problem increases, the search space becomes larger and more complex, which is where Gas may outperform other algorithms. Genetic Algorithms have found various applications in logistics, where optimization problems with complex solutions are frequently encountered. These problems can include routing optimization, vehicle scheduling, load balancing and inventory control, among others.

Moreover, in literature, when applied to routing problems, its performances were greatly improved when Hill Climbing Algorithm was used to further optimize its results.

The authors in [27] analyzed the Vehicle Routing Problem and designed a Dynamic Vehicle Routing Problem with Time Windows (DVRPTW) model and solved it using a Genetic Algorithm. The solution was then further optimized by a hill climbing algorithm. The results showed that the improved GA algorithm had better performance in optimizing the distribution route, reducing the total cost of planning by 31.44% compared to the GA algorithm and increasing the cost by 11.48% considering the traffic network data. The study considered the influence of the urban traffic network on logistics distribution and the use of real-time traffic data (vehicle speed) in the traffic network to improve the efficiency of logistics distribution. The authors concluded that the improved GA algorithm has good performance and can significantly reduce the cost of distribution and that studying VRP based on traffic network data is more in line with the actual situation of logistics distribution.

In [28] the authors study a routing problem for electric vehicles while taking into account the limitations on battery life and the availability of battery swapping stations. The algorithm is built such that it minimizes the total expenses associated with energy consumption and travel time for electric vehicles. To solve this model effectively, an adaptive genetic algorithm that is based on hill climbing optimization and neighborhood search is implemented. The results show that a routing solution that takes into account power consumption and travel time can decrease carbon emissions and lower overall delivery costs for logistics.

In literature Gas have also been applied to different problems than those described in 2.1, but not less important for the performances of the logistics operations of the companies, such as resource allocation and warehouse design.

Paper [42] is about the optimization and simulation of a production/inventory system that consists of a workshop and warehouses. The goal of the research is to allocate resources appropriately to meet the “Just-in-Time” (JIT) mode of the core manufacturers. The researchers have constructed a logistics simulation model for the system and have designed an immune evolutionary algorithm to resolve the resource allocation problem. The algorithm was able to achieve the optimal result for the key resources allocation problem, including inventory of both materials and transport equipment.

Considering warehousing, the authors of [48] describe a multi-objective hybrid genetic algorithm for optimizing the layout of a warehouse. The optimization goals are to improve the efficiency of the warehouse, to take into account the turnover rate of the goods and the stability of the shelves. In order to improve storage efficiency, it is necessary to shorten the time of goods out of storage and to shorten the picking path. While to improve shelf stability it is necessary to lower the shelf center of gravity and to balance the shelf stability across its axis. Applying the algorithm to an e-commerce company warehouse the three optimization goals have been reduced by 46.19%, 9.16%, 4.40% respectively.

2.3.4.2. Particle Swarm Optimization

The Particle Swarm Optimization (PSO) algorithm was first introduced by Eberhart and Kennedy based on the study of the foraging behavior of birds. As mentioned in the original paper, sociobiologists believe a school of fish or a flock of birds that moves in a group "can profit from the experience of all other members".

It is a type of Evolutionary Algorithm that uses a swarm of particles to move gradually towards an optimal solution. The algorithm is driven by randomized modification operators and the interaction between the particles.

At the start of the process, a number of random points on the plane are defined as particles. These particles move in random directions to search for the minimum point in the solution space. Each particle searches around the minimum point it has ever found, as well as the minimum point found by the entire swarm of particles. The swarm is guided by the best individual in the population and the local memories of each particle. After a set number of iterations, the minimum point of the function found by the swarm is considered the optimal solution.

PSO has several advantages, including its simplicity, fast convergence speed and strong universality. It requires a few parameters to be adjusted and uses a collaborative search method, making use of both individual and population extremums to guide the search. PSO is typically able to converge to local or global optima [45].

The authors of [45] discuss the application of two multi-objective evolutionary algorithms for solving the Inventory Routing Problem (IRP) in logistics. The IRP is a multi-period distribution problem that involves two components: the inventory management problem and the vehicle routing problem. The goal is to minimize both distance cost and inventory cost and sometimes also to minimize the risk of stock-out, which is considered as a third objective function. The authors compare the performance of two algorithms, the Steady-State Multi-objective Simultaneous Evolutionary Algorithm (SMS-EMOA) and a multi-objective particle swarm optimization (PSO) algorithm, in finding the Pareto optimal front of the problem.

The results of the study suggest that both algorithms can generate good approximations of the Pareto front, but the performance of each algorithm may strongly depend on the specific problem instance and the parameter settings.

2.3.5. Artificial Neural Networks

The artificial neural network (ANN), also known as simply a neural network, is a machine learning technique that has evolved from the idea of simulating the human brain. The human brain is composed of a vast number of interconnected neurons, each of which performs a simple task, such as responding to an input signal. However, when these neurons are interconnected, they are capable of performing complex tasks, such as speech and image recognition, with impressive speed and accuracy.

Just like the biological neural network, the ANN is an interconnected network of nodes, which can be thought of as analogous to neurons. Each neural network has three crucial components: node character, network topology and learning rules:

1. Node character determines how signals are processed by each node, including the number of inputs and outputs associated with the node, the weight associated with each input and output and the activation function.
2. Network topology determines the way nodes are organized and connected.
3. Learning rules determine how the weights are initialized and adjusted.

Each node receives multiple inputs from other nodes via connections that have associated weights, similar to the strength of synapses in the biological neural network. When the weighted sum of inputs exceeds the threshold value of the node, it activates, passes the signal through a transfer function and sends it to neighboring nodes.

The nodes are organized into linear arrays, known as layers. There are usually three types of layers in a neural network: input layers, output layers and hidden layers. Designing the network topology involves determining the number of nodes at each layer, the number of layers in the network and the connections among the nodes. These factors are typically set by intuition and optimized through multiple cycles of experimentation.

During training, the hyperparameters of the model are tuned, adjusting the weights to minimize the error between the network's output and the correct output.

ANNs are well-suited for a variety of applications and different versions perform better for specific types of problems. For instance, image processing applications have been shown to benefit from Convolutional Neural Network (CNN) models. The main component of a CNN is the convolutional layer, which features local connectivity patterns that force the network to operate on limited receptive fields [10].

Neural networks have been applied to logistics to improve processes, reduce costs and increase efficiency. Starting from the Vehicle Routing Problem, the authors in [5] examine the efficacy of a simplified neural network model in comparison to five commonly used routing heuristics methods in the logistics field. This study utilizes a real-world simulation of the Hamburg Harbor Car Terminal, which handles approximately 46,500 vehicle routing decisions each year. The results show that the neural network model outperforms the best heuristic by 48% in terms of efficiency and when the complexity of logistics increases and decision-making becomes more flexible, the neural network model improves routing decisions by three times more than the top-performing heuristic.

The study in [34] again proposes a vehicle routing optimization algorithm based on Hopfield neural networks for logistics distribution. The authors construct a mathematical model for the VRP and use Hopfield neural networks to solve the optimization problem and perform a simulation experiment using Matlab, analyzing the results in terms of performances. The results show that the algorithm is efficient and accurate, with fast convergence.

Most importantly, as mentioned earlier, ANN models are useful for their capability to be used to recognize and interpret images and pictures. For instance, in [10] the authors propose an approach for autonomous warehousing inventory management that uses unmanned aerial vehicles equipped with environment sensing cameras and computational power to perform real-time inspection and recognition of package labels and barcodes. The goal of this approach is to enable an autonomous warehouse inventory system, where drones can localize and recognize packages in stock and signal any missing or decrease in the supply of certain products. The experiments carried out in real warehouse environments showed that high precision can be achieved with an average precision of over 80% by using light Convolutional Neural Network (CNN) models.

The results from literature are summarized in

Table 7 with a more precise classification depending on the area of application of the algorithm. The results confirm how some algorithms are more suitable to certain types of problems according to their characteristics.

Artificial Neural Network, while it is the only algorithm used for image recognition, is not so popular for delivery routing or material handling systems routing.

Reinforcement Learning appears to be very versatile and its characteristic of learning interacting with the environment allows its application in the different problems involving delivery routing.

Also Ant Colony Optimization is applied to various problems in literature, it has been studied for delivery routing and material handling system routing.

Hill climbing algorithm on the other hand is mainly used as an additional optimization method on the result obtained by other algorithms.

	Delivery Routing	MHS	Picking	Inventory	Inbound Logistics	Warehouse Management
Neural Networks	(Wei M, Bin Y, 2011)			(De Falco et al., 2019)	(Becker T et al., 2016)	
Reinforcement Learning	(Jiang J et al, 2021)	(Jeong Y et al, 2021) (Govindaiah S, Petty M.D, 2021)	(Yusuke K et al., 2019)			
Genetic Algorithm	(Das D N et al., 2021) (Yang Z et al., 2015)	(Wang X et al., 2007)				(Qiaohong Z, Yanchan L, 2021)
Hill Climbing Algorithm	(Li H. H et al., 2021) (Li J. et al., 2020)					
Ant Colony Algorithm	(Aswani R. et al., 2018) (Bell J. E, McMullen P, 2004)	(Hu M. et al., 2021)	(De Santis R. et al., 2018)			
Particle swarm optimization	(Yang Z et al., 2015)					

Table 7: Classification of AI algorithm application to logistics.

3 Methodology

The section is divided into three parts: a first part outlining the purpose of the analysis and the research activities carried out (Section 3.1) and a second part describing the methodology of the analysis (Section 3.2);

3.1. Purpose of the analysis

From the analysis conducted thus far, it has become apparent that a crucial aspect of examining the use of Artificial Intelligence in logistics is being overlooked – the evaluation of sustainability implications. While AI is known to increase efficiency, reduce costs and improve the overall productivity of logistics operations, it is imperative to provide a methodology to evaluate its impact on sustainability.

These motivations lead to the following research question: How AI can be applied in logistics to maximize sustainability-related benefits and how to measure benefits?

Specifically, the literature review aimed to determine if existing KPIs for the evaluation of sustainability in logistics could be applied to assess the ability of AI to improve the sustainability impact of companies. The thesis aims to explore the perspectives of companies on evaluating their positive or negative impact on the sustainability pillars (social, economic and environmental) by applying AI to logistics operations.

To achieve the research objectives, the study began with a review of the literature on the evaluation of sustainability in logistics and the application of AI and then followed by interviews with 4 Italian companies.

3.2. Case study analysis

This part of the study involved the collection of qualitative data through interviews with companies. The purpose of the interviews was to explore the perspectives of companies on evaluating the sustainability impact of AI in logistics.

3.2.1. Significance of the problem

Sustainable logistics practices are crucial for companies to reduce their environmental impact, meet regulatory requirements and enhance their brand reputation. Artificial intelligence has the potential to improve sustainability in logistics by optimizing its processes. However, as mentioned earlier, there is a lack of literature on evaluating the sustainability performance of AI solutions in logistics. This chapter aims to highlight the significance of this research problem.

Understanding how companies evaluate the sustainability improvements brought by the application of AI in logistics is significant for several reasons. These evaluations not only inform decision-making but also contribute to the development of sustainable logistics practices and drive industry-wide change.

Firstly, evaluating sustainability impacts allows companies to identify the potential benefits and drawbacks of different AI solutions in terms of sustainability. The comparison of different applications and the analysis of their environmental, social and economic impacts, companies can make informed decisions about which technologies to adopt and how to integrate them into their operations. This knowledge helps them to optimize their logistics processes, minimize negative impacts and maximize positive contributions to sustainability.

Secondly, by systematically assessing these aspects, companies can develop more effective sustainability strategies that align with their business goals and address stakeholder concerns, ensuring that AI-driven logistics solutions contribute positively to the triple bottom line.

Thirdly, understanding how companies evaluate sustainability improvements brought by AI can inform the development of robust evaluation frameworks, providing standardized metrics and methodologies for measuring performance. Such frameworks promote transparency and comparability across the industry, allowing companies to benchmark their efforts and identify areas for improvement.

Finally, it can inform policymaking by providing insights into the effectiveness of existing regulations and incentives for promoting sustainable logistics practices and identifying areas where new policies and incentives may be needed.

Providing policymakers with reliable data, they can make informed decisions on the benefits and potential trade-offs of AI in logistics to set targets and regulations. Thanks to the identification of the areas where AI can have the greatest positive impact, policymakers can develop specific policies to incentivize the adoption of AI within the logistics sector which promotes sustainable development and encourages businesses to prioritize environmentally friendly practices.

Most importantly, evaluating the effectiveness of AI applications in logistics helps policymakers prioritize investments in areas that offer the highest sustainability returns, ensuring that public funds are used effectively to drive positive change within the industry.

3.2.2. Objectives and role of the existing literature

This case study research aims to contribute to the understanding of how companies evaluate the sustainability improvement brought by the application of AI in logistics and to provide insights that can inform the development of more sustainable logistics practices. However, further research questions may be addressed during the interviews. The additional objectives that these questions will create include:

1. To identify the AI applications used by companies in logistics that have possible sustainability implications.
2. To explore the perspectives of companies on the sustainability implications of their AI solutions in logistics.
3. To examine the challenges and opportunities associated with evaluating the sustainability impact of AI solutions in logistics.
4. To develop a framework for evaluating the sustainability impact of AI solutions in logistics that can guide companies in their sustainability assessments and inform policymaking.

While literature is present on the methods for evaluating the sustainability impact of logistics operations, including transportation and warehousing, there is a lack of research on how these methods can be applied to companies that are implementing AI solutions in their logistics operations.

This research gap is significant, as it limits the ability of companies to assess the sustainability implications of their AI solutions and make informed decisions about their logistics operations.

Therefore, the current study aims to fill this gap by examining how companies that are implementing AI solutions in logistics evaluate the sustainability impact of their operations.

3.2.3. Methodology

3.2.3.1. Unit of Analysis

The unit of analysis for this research were single companies that have either implemented artificial intelligence solutions to improve their logistics operations or developed AI solutions for logistics. These companies may need to assess the sustainability implications of the solutions they applied or be interested in measuring the sustainability implications of the solutions they propose for marketing purposes.

Research was conducted to identify AI solutions in logistics and AI applications with possible sustainability implications were identified through an internet search using the keywords "AI", "Logistics", "Warehousing", "Inventorying", "Solutions" and "Routing".

Only the solutions that met the inclusion criteria of being applied to the logistics sector with possible sustainability implication were selected.

The companies that developed the selected AI solutions were then contacted via email, requesting details on their AI solutions and their availability for a brief video interview. A total of 50 companies applying AI to logistics were contacted.

The sample that originated from these inclusion criteria included companies of different sizes, ranging from large multinational corporations to smaller ones. Additionally, both well-established companies and newer ventures were included in the sample.

Most importantly, companies were selected based on their availability and willingness to participate in the study.

3.2.3.2. Data Collection

The primary data collection method for this study was semi-structured interviews.

Prior to the interview, the participants were informed about the purpose of the study and their consent was obtained.

The interviews were conducted using a semi-structured interview guide, which was developed based on the research questions. The interview guide included questions on the companies' approach to evaluating sustainability in logistics, their experience with AI in logistics and the AI algorithms used by their applications. The interviews were conducted through video conferencing.

The 7 questions asked during the interviews were the following:

- How did the processes take place before the adoption of AI?
- What spur the change towards AI? Which were the drivers that led the company to this change?
- Which are the benefits of your solutions in terms of sustainability? Do you measure them?
- How do you measure the benefits brought in terms of sustainability?

- Do you communicate those benefits to your customers?
- Have you got any sustainability objectives in general?
- Do you evaluate your impact on the environment? Do you use AI for this purpose?

4 Findings

The aim of these case studies is to investigate how companies measure the sustainability implications of applying Artificial Intelligence (AI) to logistics.

This chapter will present the key findings from the remaining four companies and discuss their implications for the industry.

The companies that responded to the case study analysis were all Italian small to medium-sized companies that specialize in providing AI solutions to various industries. Most of the companies were founded in recent years, demonstrating the growing interest in AI and its potential applications.

4.1. Ally Consulting and U-Hopper

Ally Consulting is an Italian consulting firm established in the 1990s, specializing in the implementation of ERP management systems. The company's primary customers are small to medium-sized manufacturing companies seeking to optimize their operations and improve their performance.

In recent years, the company has recognized the limitations of ERP solutions to fully leverage digital transformation and has explored the possibilities and benefits of integrating AI solutions to improve its services. To achieve this, Ally Consulting formed a partnership with U-Hopper, a "Data Intelligence Lab" that emerged in 2010 as a startup of the international research center Fondazione Bruno Kessler.

U-Hopper is a leading player in the development and implementation of AI and ML solutions, with a primary focus on providing data-driven solutions that enable companies to make better decisions and optimize their processes. Through this partnership, Ally Consulting aims to harness U-Hopper's expertise to enhance its offerings, provide cutting-edge AI solutions to its clients and integrate these solutions into the ERP systems they implement.

Solutions

Several solutions developed by Ally and U-Hopper involve logistics. U-Hopper's AI solutions for inventory optimization are aimed at establishing the optimal reorder point for their clients by using Markov Chain Models, for which the probability of an event only depends on the previous state of the system. By optimizing the inventory level, companies can avoid overstocking or understocking, which can lead to unnecessary waste or shortages, respectively. Therefore, these solutions help companies reduce costs and inventory levels, leading to a positive impact on the company's sustainability performance by reducing both costs and waste.

Ally and U-Hopper are also developing AI-powered solutions to help companies find the best mode of transportation for their goods. The algorithms used in these solutions are not disclosed, but they consider factors such as the type of goods being transported and the distance to the delivery point to suggest the optimal transportation mode. These solutions help companies reduce transportation costs and emissions, while also ensuring timely delivery of perishable goods, reducing waste.

They also aim to optimize Warehouse operations thanks to the use of AI and pattern recognition. The Co-Founder of U-Hopper brought the case study of a FMCG (Fast Moving Consumer Goods) company, with 0.5 Billion of yearly revenues. The company was facing problems due to perishable goods being inside the warehouse. From data collection and pattern recognition, U-Hopper was able to identify the problems and increase marginalities by 6%.

U-Hopper is also working on predictive maintenance, which involves analyzing data to predict when maintenance will be needed on a piece of equipment before it fails. U-Hopper developed a predictive maintenance algorithm for a maintenance company that services a renewable energy provider's solar park. The maintenance company had been performing programmed maintenance, which resulted in several trips to check the status of the plant that were unnecessary and went unpaid. U-Hopper's algorithm analyzed data before each failure and implemented a Markov Chain Model, which allowed the maintenance company to predict when maintenance was needed and renegotiate the contract with the renewable energy provider. The algorithm not only improved the reliability of the solar plant but also reduced emissions and costs associated with unnecessary maintenance interventions.

Measurement of sustainability aspects

As of now, the sustainability aspects of their solutions are not studied as they are still focused on the implementation and the optimizations of their applications.

However, these aspects might become relevant for their customers, as a reduction in emissions or waste generated leads to a reduction of the Carbon Tax, as well as for marketing purposes.

Moreover, the measurement of the sustainability aspect would require a long period of observation and very accurate data collection and analysis. This would require a change in the processes inside the companies and would impact on their organization.

To sum up, Ally and U-Hopper's AI-powered solutions are aimed at helping companies optimize their inventory levels, reduce transportation costs and emissions and improve warehouse operations. The company also developed a predictive maintenance algorithm for a maintenance company that services a renewable energy provider's solar park, which resulted in improved reliability, reduced emissions and costs associated with unnecessary maintenance interventions.

While the sustainability aspects of their solutions have not been studied yet, they may become relevant for customers in the future as a reduction in emissions or waste leads to a reduction in the Carbon Tax and can be used for marketing purposes. However, measuring sustainability aspects requires accurate data collection and analysis, which would require a change in the processes inside the companies and would impact their organization.

4.2. Oltre Solutions

Oltre Solutions is a small Italian company that is specialized in providing its customers with an ecosystem of solutions for data collection, aggregation and processing. With extensive field experience in industrial engineering and industrial production process design and management, Oltre Solutions is positioned to help its customers optimize their logistics operations. During the interview, the company's Load Manager solution was the main focus of discussion.

Solutions

The Load Manager solution is an application that was developed in 2016 and is designed to optimize the scheduling and planning of loading and unloading activities within a warehouse. The solution focuses on optimizing the use of bays, gates and any other scarce resources in the system, both for inbound and outbound flows. Load Manager is a finite-capacity scheduler that manages the time dimension of the resources, each with its own constraints related to the type of goods, available operators and time occupied by a vehicle that performs loading and unloading activities until the bay is cleared for the next activity.

The traditional method of scheduling loading and unloading activities involves defining an average time for the process, which does not consider the nature of the goods transported. This results in a loss of efficiency of around 40-50%. Additionally, warehouse reservations of the bays will only saturate two-thirds of the workday, as a way to compensate for delays and inefficiencies in the remaining time. Oltre Solutions analyzed data from their clients and found that vehicles for deliveries and pick-ups of goods were on time only 20% of the time, early 60% of the time and late for the remaining 20%.

To address these inefficiencies, the Load Manager solution proposed, dynamically renegotiate the slots assigned and assigns a specific duration based on the nature of the goods transported. By considering the specific attributes of each shipment, Load Manager can schedule the most efficient use of the bays and optimize the use of scarce resources within the warehouse. This dynamic scheduling results in higher efficiency and cost savings, ultimately leading to improved overall logistics operations.

To ensure the accuracy of the system, precise and timely data collection is necessary. This data includes information such as the position of the vehicle, the company it comes from and the time in which it entered the system, which are collected using QR codes. The collected data is then used by the algorithms to build a digital twin of the warehouse and yard, which is utilized by a "Virtual Concierge" website through which suppliers and clients can book their slots.

To predict the precise duration of the loading and unloading operations, the algorithms utilize a combination of historical data, both from the same customer and from their entire customer base. The data gathered inside the warehouse for each operation include the quantity of handling units, the origin of the handling unit, material characteristics and whether the operation was loading or unloading. These data are then fed into AI algorithms to predict the duration of the operations. If the deviation between the predicted and actual operation time is considered too significant, the solution can dynamically adjust and self-correct.

The CEO of Oltre Solutions notes that the solution is dependent on the availability of data. Therefore, an initial hybrid solution is necessary for the first few months after the implementation of the application. Initially, average values with little variability are used, while later, after sufficient data have been obtained, ML models are used to ensure the precision and accuracy of the system.

A researcher of the company conducted a study on the algorithms used in the Load Manager solution. He reported that the main challenges were related to the complex data preparation process and the lack of documentation on applying AI algorithms to the logistics field. The study focused on supervised regression methods, as the objective was to predict time measures, making classification techniques unsuitable.

The main algorithms studied were:

1. Linear regression
2. Decision Trees and Boosting
3. Support Vector Regressors
4. Neural Networks

The evaluation showed that the boosting technique produced the smallest errors. This may be attributed to the high number of categorical variables in the data. The algorithms that performed the best were LightGBM and CatBoost, developed by Microsoft and Yandex respectively.

In terms of results achieved by Load Manager, the company claims a reduction in warehouse downtime of 30%. Moreover, a reduction in vehicle throughput time by almost 50% has been achieved.

Measurement of sustainability aspects

Although the company does not measure the sustainability implications of using Load Manager, the CEO believes that the solution's implementation has led to significant efficiency improvements and reduced throughput time. As a result, the global vehicle fleet could potentially be reduced by approximately 25%, which would result in significant savings due to the non-production of excess vehicles required to absorb inefficiencies.

Moreover, the reduction in waiting time for vehicles, particularly refrigerated trucks, could result in a significant reduction in pollution emissions as these trucks generate emissions while keeping the desired temperature.

To summarize, the company does not have a direct measure of sustainability. However, the implementation of Load Manager has produced a range of environmental benefits, which will likely have a positive impact on the company's overall sustainability goals.

4.3. Regesta

Regesta is an Italian consulting firm, founded in Brescia in 2007, with the primary objective of supporting companies in their digital transformation through the implementation of ERP solutions. It has around 200 employees and has developed IT solutions for various companies both inside and outside Italy. In 2017, the company began implementing IoT technologies in its solutions, showing a growing interest in data analysis.

In 2020, Regesta Lab was born, a company of Regesta Group specialized in the development of advanced and predictive analytics, IoT, machine learning and advanced planning solutions. The aim of Regesta Lab is to optimize the processes of its clients in a smart and data-driven way, providing them with innovative and customized solutions. The company's mission is to help its clients increase their efficiency, reduce costs and improve their overall performance. Their main customers are manufacturing companies, steel mills and metallurgical companies.

The company provides several AI solutions to optimize the logistic activities of its clients.

Solutions

Starting from the solution to create a Digital Twin of the client's plant, the company uses mainly XGBoost and Neural Networks algorithms, but plans to use Reinforcement Learning in the next projects as the amount of data necessary to train the model is significantly lower than with other algorithms. This solution, applied in the process industry, might significantly improve the company sustainability performance. Using real-time data and simulations in different scenarios, digital twins can identify areas for improvement in energy efficiency, optimization of the processes and resource management, allowing organizations to make more informed decisions and reduce their environmental impact.

Regesta Lab also offers a solution for the weigh station of steel mills. One of the most energy intensive processes in these companies is the melting of scrap iron into the furnace. Thanks to a Computer Vision algorithm which analyzes the content of trucks and recognizes the type of iron, the different cargos are addressed to the right bay for the delivery of the metal. The results achieved thanks to this operation as well as the potential sustainability benefits are significant, as this solution not only reduces energy consumption for the melting process by improving the sorting of materials but also reduces throughput time, thereby reducing costs for the company and minimizes material handling operations inside the plant, resulting in reduced emissions generated by this activity.

The company also provides a solution for Inventory optimization. This involves two steps, the demand prediction, using regression algorithms and the inventory level optimization, performed using Operative Research models. However, demand prediction algorithms struggle with steel mills companies, as the demand it's not influenced by seasonality, price and other factors that can be evaluated with a certain degree of precision, but depends on political and macro economical aspects, much more difficult to predict.

Measurement of sustainability aspects

According to Regesta, when it comes to measuring the positive sustainability impact of their AI solutions, their clients do not require precise measurements and such activities are considered secondary.
The reason for this is that, even if every company is required to produce an ESG balance sheet, it includes estimates of the sustainability impacts from a wider perspective, making them easier to obtain and control. However, the ESG department of an Italian company typically is not yet able to measure the impact of individual projects or AI solutions. This is because it requires a large amount of data that can be difficult to gather and there are currently only a few data-driven companies capable of performing such measurements.
To measure the sustainability implications of individual solutions, significant changes and improvements are needed in the integration and communication between different systems. Companies estimated that it may take at least 10 years to see these changes occur in the Italian industry. Until then, it may be challenging for companies to communicate and measure the sustainability impacts of their solutions in a precise manner.

To summarize, Regesta Lab does not currently measure or communicate the sustainability implications of their solutions, which include digital twins for process optimization, a weigh station sorting solution and inventory optimization. Even though these solutions have clear sustainability improvements, such as reducing energy consumption and emissions, improving efficiency and reducing waste. The difficulty in gathering the necessary data for precise sustainability measurements and the need for significant improvements in system integration and communication pose challenges for such measurements.

4.4. Wenda

The company, born as a Foodtech startup in 2015, with the objective of using IoT devices to allow the tracking of wine products, has evolved to become a provider of a SaaS platform that aggregates data from different sources and devices, creating an integrated view of logistics operations and enabling the automation of workflows.

Solutions

By connecting with different systems and devices of the company, such as the ERP, WMS and TMS, as well as RFID readers, data loggers and other devices via API, the platform analyzes data and creates automated workflows.

To extract information from documents, emails and data, proprietary OCR algorithms are utilized to digitize data. After digitization, proprietary Natural Language Processing algorithms are employed to standardize and categorize data. The solutions can recognize product type, quantities and container sizes and enable container tracking thanks to integration with other tracking service providers. For example, by analyzing a packing list received by email, the solution can provide users with container tracking.

Additionally, the company offers route optimization solutions, though the specifics of these algorithms were not disclosed during the interview. The company also provides an inventory optimization solution that utilizes OCR and NLP algorithms to improve collaboration with suppliers, allowing for more precise and timely inventory management.

The solutions proposed by the company might have significant positive sustainability implications. Thanks to the inventory optimization solution, a reduction in waste and costs is expected. Moreover, the routing optimization solution will significantly help to achieve a reduction in fuel consumption, which will result in fewer emissions, less costs for the company and an improvement in traffic congestion for the community.

Measurement of sustainability aspects

However, the interviewee noted that the company does not currently measure the sustainability aspects of their solutions, nor do they mention the positive sustainability implications to their clients. The interview also revealed that the company is still exploring these aspects of their solutions.

Overall, the company's SaaS platform provides a holistic view of logistics operations and enables automation of workflows, which can increase efficiency and productivity. The use of OCR and NLP algorithms to extract and categorize data adds an additional layer of precision and accuracy to the solutions, with the potential to reduce waste and inefficiencies. The measurement of the sustainability implications of their solutions, however, is overlooked.

In conclusion, the companies interviewed in this study have developed or implemented AI-powered solutions that are aimed at improving logistics and supply chain operations. However, despite the potential sustainability benefits of their solutions, none of the companies have yet measured the sustainability implications of their solutions.

While the companies acknowledge that sustainability is an important issue, they are still focused on the implementation and optimization of their applications. Furthermore, measuring sustainability aspects would require a significant change in the processes inside the companies and require significant improvements in the integration of the systems.

It is important for companies to start considering the sustainability implications of their solutions as it can lead to reduced costs, taxes and better marketability.

Table 8 presents a summary of the information gathered from the interviews conducted.

Table 8: Summary of the interviews

	Logistic Operations Addressed	Algorithms	Measures Sustainability	Challenges of the measurement	Possible benefits of the mesurement
Ally Consulting and U-Hopper	Delivery, Inventory, Warehousing, Predictive Maintenance	Markov Chains	No	Focused on the implementation of the solution, long time required to evaluate the effects, changes in company processes needed	Reduced taxes, green certifications, marketing purposes
Oltre Solutions	Inbound Logistics, Material Handling	Decision trees and Boosting	No	Difficult to precisely evaluate savings in term of emissions	Not mentioned
Regesta Lab	Inbound Logistics, Inventory, Material Handling	Regression models, XGBoost and Neural Networks	No	Large amount of precise data required, better integration and communication needed between the systems of the company	Marketing purposes
Wenda	Inventory, Delivery Routing, Tracking	NLP and OCR algorithms	No	Focused on the implementation of the solution	Not mentioned

5 Discussion and Conclusions

This chapter provides a comparison of the data collected through interviews described in chapter 4, against the findings of the literature review. The interviews focused on understanding the AI solutions developed by these companies and their potential sustainability implications. Paragraph 5.1.1 will deep dive on the algorithms implemented by companies in their solutions. Paragraph 5.1.2 will study the AI solutions developed by the companies and their potential impact on sustainability. Paragraph 5.1.3 will analyze the challenges associated with measuring sustainability outcomes. Additionally, the chapter concludes with a discussion of the overall implications of the study's findings and suggests areas for future research on AI and sustainability in logistics and transportation.

5.1. Discussion

5.1.1. Algorithms and solutions

The literature reveals different AI algorithms applied to optimize the various logistics processes. However, the interviews conducted report fewer applications in practice. This discrepancy may be attributed to the limited number of companies participating in the interviews and their reluctance to adopt newer, less known applications. Literature often explores cutting-edge and experimental solutions, while companies prioritize implementing proven, reliable technologies. The cautious approach taken by companies can be understood, as they focus on achieving tangible benefits and minimizing risks. Therefore, the adoption gap between theoretical advances and real-world implementation highlights the need for further exploration and validation of novel AI applications in logistics.

5.1.1.1. Inventory

The main algorithm found in literature to optimize inventory is artificial neural networks (ANN). In paper [10], ANNs were used to analyze images coming from cameras to precisely measure inventory levels of the company.

However, from the interviews, a popular application of AI to optimize the management of inventory and of the warehouse is demand prediction. To predict the demand of B2C companies, Regesta Lab uses Regression models. Regression models use both data on product sales and variables such as price, promotions, seasonality and economic indicators, to estimate the relationship between these variables and demand and then predict the future sales of products. These models can also be customized including different variables to account for external factors such as product substitutes and customer preferences. This allows companies to develop more accurate and relevant demand forecasts that reflect the unique characteristics of their products and markets.

Regression models also have some limitations for demand forecasting. One limitation is that they strongly rely on historical data, which may not be indicative of future demand. For example, unexpected changes in the economy or consumer behavior can impact demand in ways that are not captured by the historical data. Another limitation of regression models is that they require a significant amount of data to train and provide meaningful results.

U-Hopper and Ally use Markov Chains to address the problem of defining the optimal reorder point for the company. The reorder point is the inventory level at which a company should place an order to replenish its stock.

Using a Markov chain model, a company can estimate the probability of the inventory level falling below the reorder point during the lead time, which is the time it takes for a new order to be delivered.

The Markov chain model works by representing the inventory level as different states, with each state representing a specific inventory level. The model can also take into account the demand rate, the lead time and their variability to determine the optimal reorder point.

The probabilities of transitioning between different states are determined by different factors. Then, by analyzing the probabilities of transitioning between states, the model can estimate the probability of the inventory level falling below the reorder point during the lead time and allow the company to take more informed decisions on the management of inventory.

Wenda applies techniques to optimize inventory operations and to precisely monitor stock levels. Thanks to Optical Character Recognition techniques and Natural Language Processing, their platform is able to precisely track material and quantities received by suppliers and thanks to a pervasive integration of systems, the supplier will know when the company will need to replenish its stocks.

Therefore, from the interviews conducted with the companies, it was found that various technologies are being employed to optimize inventory, including regression models, Markov chains and OCR algorithms. These methods have been used to establish the optimal reorder points for clients, reducing costs and inventory levels and thus having a positive impact on sustainability by reducing waste. On the other hand, literature review has shown that a limited number of algorithms are used to optimize inventory, with Artificial Neural Networks that have also been used for image recognition, which is similar to the Optical Character Recognition (OCR) algorithm proposed by Wenda. The OCR algorithm is used for recognizing text from images, while artificial neural networks are used for pattern recognition in images.

5.1.1.2. Inbound Logistics

The main algorithm found in literature to optimize inbound logistic operation was artificial neural networks. In [5] the authors examine the efficacy of a simplified neural network model in comparison to five commonly used routing heuristics methods in the logistics field, outperforming the best heuristic algorithms by 48% in terms of efficiency.

To address the problem of optimizing inbound logistics operations Regesta Lab, instead, implemented a Computer Vision algorithm. As scrap metal is a crucial input for steel production, it is essential to optimize its management and ensure the correct classification of the materials entering the plant. To achieve this, Regesta Lab is using a Computer Vision algorithm, the details of which have not been disclosed, to recognize and classify the type of scrap metal entering the steel mill plants.

By analyzing the images of the materials, the algorithm can determine the specific characteristics and properties of each type of scrap metal, such as its size, shape and weight. This information is then used to optimize the management of the materials and streamline the inbound logistics processes.

Oltre Solution, instead, is using Decision Trees and Boosting to accurately plan the loading and unloading of trucks in the company yard. Decision Trees and Boosting techniques are commonly used in machine learning to optimize complex decision-making processes.

Decision trees work by breaking down a complex decision into a series of simpler decisions, each represented by a node in the tree. The algorithm then moves through the tree, selecting the optimal decision at each node, until it reaches the end of the tree and outputs the final decision.

Boosting works by combining a set of weak learners, such as the previously mentioned decision trees, to create a more accurate final model. This can help Oltre Solutions to make more precise predictions about the time required for each truck to be loaded and unloaded, taking into account a variety of variables such as the type of goods being transported and the availability of resources.

The findings of the interviews conducted with companies and the literature review differ in terms of the methods used for optimizing inbound logistics operations. The literature review highlights the use of artificial neural networks, which were able to outperform the best heuristic by 48% in terms of efficiency. In contrast, the companies interviewed are using different technologies for the optimization of their operations.

These differences may be due to the fact that, as mentioned before, the companies are using existing technologies that have been proven to be effective, while the literature review explores newer, more advanced solutions that may not yet be widely implemented in the industry. This suggests that while there is potential for further innovation in inbound logistics optimization through the use of AI, companies may also benefit from exploring and implementing existing solutions that have already demonstrated effectiveness.

5.1.1.3. Digital Twin

A digital twin of a company is a virtual representation of a physical organization that uses real-time data and simulations to reflect the current state and predict the future behavior of the company. It incorporates data from various sources to provide a comprehensive view of the company's operations, processes and performance.

It enables companies to test and optimize different scenarios and strategies without disrupting the actual production process. It can also help companies identify potential problems and opportunities, improve operational efficiency, reduce costs and analyze the impact of various factors on the company's performance.

To optimize the processes inside the companies Regesta Lab is implementing Extreme Gradient Boosting Algorithms (XGBoost) and Neural Networks. Both algorithms are powerful machine learning techniques that can be utilized in a digital twin of a plant to optimize plant performance and improve efficiency.

XGBoost is an optimized implementation of the gradient boosting algorithm that is commonly used for supervised learning problems, such as regression and classification. It uses an ensemble of decision trees, where each tree is trained to predict the residual error of the previous tree. It can be used to model complex relationships between different variables in the plant and to predict future outcomes based on historical data. In a digital twin of a plant, XGBoost can be used to optimize processes such as production planning, scheduling and maintenance. While Neural Networks have been described in chapter 2.3.5.

The literature analyzed in this thesis did not include digital twin solutions such as the one implemented by Regesta Lab, which suggests that the companies interviewed may also have applied AI to a different logistics operation than those discussed in the literature.

5.1.2. Sustainability implications of the solutions

This paragraph is going to analyze the sustainability implications of the solutions implemented by the companies interviewed, already mentioned in chapter 4, comparing them with the findings from the literature in chapter 2.1.2.

The literature analyzed in the thesis reveals that the implementation of AI algorithms in logistics operations offers numerous sustainability benefits. These advantages span across various dimensions of sustainability, encompassing economic, environmental and social aspects. AI-driven logistics operations enhance efficiency and effectiveness, fostering sustainable growth while minimizing resource usage. Moreover, they facilitate better decision-making and adaptability in complex supply chain environments. Many logistics operations have been found to be greatly optimized by the usage of AI, one of these is inventory optimization.

As seen in the previous chapters, three out of four companies interviewed, Ally and U-Hopper, Regesta Lab and Wenda, provide a solution for inventory optimization. These solutions have the potential to significantly improve the sustainability performance of companies by reducing waste and minimizing the environmental impact of their operations. Thanks to the optimization of inventory levels companies can avoid overstocking or understocking, which can lead to waste or shortages of products in the warehouse. This can help reduce the amount of resources used in production, transportation and disposal of excess or expired inventory, leading to a reduction in carbon emissions, energy consumption and waste generation. Moreover AI can help companies identify patterns and trends in demand, allowing them to plan their inventory needs more accurately, which can lead to additional emissions and waste reduction.

Ally and U-Hopper also developed solutions for Predictive Maintenance and applied it to a renewable energy provider. Thanks to this solution several sustainability improvements can be achieved, both directly and indirectly. With the implementation of predictive maintenance companies can minimize equipment downtime, reducing the need for emergency repairs and the associated waste and emissions. The lifetime of equipment can be extended too, reducing the need for replacements and the associated resource use and waste generation, maintenance operations can be optimized, reducing the number of unnecessary interventions and associated emissions and costs. In the case of renewable energy providers, predictive maintenance ensures the reliable operation of their equipment, reducing the need for fossil fuel power plants as backup and associated emissions.

U-Hopper is also implementing solutions for the choice of the optimal mode of transportation. Considering factors such as the type of goods being transported and the distance to the delivery point, these solutions can suggest the most efficient and eco-friendly mode of transportation, leading to a reduction in emissions, which can have a positive impact on the environment while reducing costs for companies. Furthermore, ensuring the timely delivery of perishable goods can reduce waste, as goods are less likely to expire before reaching their destination.

Another fundamental element of goods transportation and delivery is addressed by Wenda, who offers a solution for route optimization. These solutions, as already mentioned in chapter 2.1.2.1, can help companies reduce the length of vehicle routing and consequently number of vehicles on the road, leading to lower emissions and fuel consumption, while also reducing costs. Route optimization can also help to reduce traffic congestion and improve overall traffic flow, leading to a reduction in idling and thus lower emissions.

Instead, Oltre Solutions developed a solution to optimize the scheduling of load and unload operation for trucks and vehicles in the company yard. In terms of the results achieved by Load Manager, the company claims a reduction in warehouse downtime of 30% and a reduction in vehicle throughput time by almost 50%. But the solution could help companies achieve several sustainability results. As mentioned, the optimization of yard operations can lead to a reduction in idle time for vehicles waiting to be loaded or unloaded which can lead to a decrease in fuel consumption and associated emissions, resulting in a reduction in the carbon footprint of the transportation process.

Moreover, the optimization of scheduling can lead to a reduction in the number of vehicles required to transport goods, as the optimization ensures that the available vehicles are utilized efficiently, Oltre Solutions estimates this reduction at around the 25% of the global fleet. This reduction in the number of vehicles can lead to a reduction in fuel consumption, but also of the waste and emissions resulting from the production process of those vehicles.

The digital twin implemented by Regesta Lab can help optimize energy consumption and reduce waste by simulating different scenarios and identifying the most efficient processes, but it can also help to identify possible risks and hazards in the plant before they occur.

Regesta also implemented a solution to identify and improve the sorting of metal scraps entering steel mills, which can bring several sustainability benefits. The sorting of materials leads to a reduction in energy consumption during the melting process. This is because when materials are not correctly sorted, more energy is required to melt them down, which results in higher emissions and energy costs. This solution also leads to the minimization of material handling operations inside the plant due to trucks arriving at the wrong unloading station, which results in a reduction in emissions and a reduction in throughput time.

The solutions implemented by companies, such as inventory optimization, predictive maintenance, transportation mode optimization, route optimization, scheduling optimization and simulation, are similar to those found in the literature for optimizing logistics operations. However, companies apply these solutions in more specific contexts, such as steel mills or renewable energy providers, while literature takes a more general perspective. The companies' solutions have the potential to significantly improve sustainability performance by reducing waste, minimizing the environmental impact and optimizing the use of resources. But, despite the potential positive implications, the companies may not have a complete understanding of all the sustainability benefits that their AI solutions are achieving. As a result, companies underestimate sustainability improvements brought by AI and only consider the ones from a general perspective, for the purpose of including sustainability estimates in their reports.

5.1.3. Assessment of the sustainability impact of AI Solutions

As found in the literature review, where the topic of the measurement of the sustainability benefits coming from the implementations of AI solutions into logistics operations showed a significant gap in research, despite the potential sustainability benefits brought by the implementation of AI solutions seen in the previous paragraph, companies do not measure the actual impact of such initiatives.

This is due to several reasons, as pointed out by Regesta Lab. One reason is the lack of integration between different systems and processes within the organizations, which prevents the collection and analysis of comprehensive data on the sustainability improvements brought by AI solutions. Additionally, companies may not have access to sufficiently precise data to understand the impact of a single AI solution, resulting in estimates from a more general perspective with the sole purpose of including sustainability estimates in the company's reports, without capturing the true sustainability benefits of AI solutions.

Regesta Lab also emphasized that significant changes and improvements are needed to achieve this level of integration and data precision. These changes include the adoption of advanced technologies, such as IoT and advanced analytics, as well as the development of robust data governance frameworks. However, the company also cautioned that it may take at least 10 years to see these changes occur, given the complexity of the task and the current state of data-driven companies in Italy.

According to U-Hopper, measuring the sustainability aspects of AI solutions would require a substantial period of observation and precise data collection and analysis, which would necessitate significant changes in the internal processes of companies and impact their organization. U-Hopper also notes that unless sustainability aspects become relevant to their clients, such as through a reduction in emissions or waste leading to a decrease in carbon tax, or for marketing purposes, there may be limited incentive to invest in measuring the sustainability benefits of AI solutions.

The main factor that is slowing the development of a framework to measure sustainability implications of AI solution, however, is that companies are currently more focused on implementing and ensuring the functioning of the solutions rather than taking into account all the positive effects that they may have on sustainability.

Summarizing, based on both the literature and the results of the interviews, it appears that there is a lack of emphasis on measuring the sustainability benefits of artificial intelligence solutions applied to logistics. The main reasons for this lack of interest seems to be related to the challenges of integrating different systems and processes within the organization, the lack of access to sufficiently precise data and the need for significant changes in internal processes to enable precise data collection and analysis.

While there may be a lack of literature specifically addressing this topic, the interviews provided valuable insights into the reasons behind the lack of interest in measuring sustainability benefits of AI solutions in logistics. These insights suggest that addressing the challenges of data integration, data precision and incentive structures could be critical in encouraging companies to measure and prioritize the sustainability benefits of their AI solutions in logistics.

5.2. Conclusions

The objective of this study is to investigate and analyze how companies measure the sustainability implications of applying Artificial Intelligence to logistics.

The study begins with a literature review on the benefits of implementing sustainability practices in logistics and how AI solutions might allow companies to improve their sustainability performance. Furthermore, the existing literature on Key Performance Indicators (KPIs) for measuring the sustainability of logistic operations has been analyzed, with a focus on the improvements that the implementation of AI solutions can bring to these indicators. The literature review finally analyzes the main algorithms used to optimize logistics operations and their implementation in research studies. Through this analysis, the literature review aims to provide insights into how companies could measure the sustainability implications of AI solutions in logistics.

To further investigate how companies measure sustainability, a case study analysis that involved reaching out to 50 companies of varying sizes and from different countries, has been conducted. However, only five Italian companies responded to the request for participation. The companies that agreed to participate in the study and met the inclusion criteria were interviewed to understand how they measured the sustainability implications of their AI solutions.

The findings from the interviews revealed that the companies had not yet implemented practices to measure the sustainability impacts of their solutions. Companies cited several reasons for the lack of practices to measure the sustainability implications of AI solutions. The first reason is the lack of integration between different systems and processes within the organization, which results in the inability to collect and analyze comprehensive data on sustainability improvements brought by AI solutions.

Companies also emphasized that significant changes and improvements are required to achieve integration and data precision. These changes include the adoption of advanced technologies and advanced analytics but would also necessitate significant changes in the internal processes of companies, as well as the development of data governance frameworks. However, these changes may take at least a decade to materialize, given the complexity of the task and the current state of data-driven companies in Italy. Moreover, sustainability aspects of AI solutions would require a substantial period of observation.

Companies noted that unless sustainability aspects become financially relevant to their clients, there may be limited incentive to invest in measuring the sustainability benefits of AI solutions.

Most importantly the main reason for the lack of measurement of the sustainability implications of AI solutions is that companies are currently focused on the implementation and the functioning of the solutions rather than considering the effects on sustainability.

According to the findings of the case study analysis, the measurement of the sustainability implications of applying Artificial Intelligence to logistics appears to be a far-off objective for many companies, particularly in the Italian industry.

From chapter 2.2.1, it is clear that traditional sustainability KPIs used in logistics can still be useful in measuring the impact of AI solutions. These KPIs include metrics such as fuel consumption, energy efficiency and waste generation. By tracking these metrics before and after the implementation of AI solutions, companies can see the improvements brought about by the technology.

However, it is important to note that traditional KPIs may not offer a comprehensive view of sustainability impact. This is because they do not take into account other environmental, social and economic factors. It is important to consider the full life cycle of AI solutions and their environmental, social and economic impact, from the manufacturing of hardware to the energy consumption during operation, to the negative effects after its implementation. For example, a company may reduce its carbon emissions by implementing an AI solution, but if it results in job losses or unfair labor practices, the overall sustainability impact may be negative.

Therefore, while traditional KPIs can provide a starting point for measuring the sustainability impact of AI solutions, they should be used in conjunction with more advanced methods and frameworks.

Moreover, the literature shows a wide array of AI algorithms useful to optimize various logistics processes, presenting a multitude of potential sustainability benefits. However, the interviews conducted with industry professionals reveal a smaller number of applications being utilized in practice. This gap may stem from the limited number of participating companies and their hesitance to adopt novel, lesser-known applications.

While the literature explores cutting-edge, experimental solutions, companies tend to prioritize the implementation of proven, reliable technologies to minimize risk and ensure operational success. Additionally, another difference between literature and interviews is in the understanding of potential sustainability benefits. The literature highlights an extensive range of possible benefits, whereas interviewed companies show a less comprehensive understanding of the AI-driven sustainability improvements.

This incomplete understanding among companies already implementing AI solutions in logistics processes implies a broader issue. It raises concerns that other organizations might be entirely unaware of or may overlook the positive impacts of AI on sustainability in logistics. This knowledge gap necessitates increased efforts to bridge the divide between academic research and real-world application, promoting awareness of AI's sustainability advantages in the logistics sector.

Further research is therefore needed to explore the reasons for the lack of interest and awareness regarding the sustainability implications of AI solutions in logistics. This research could focus on the different cultural, organizational and regulatory factors that may be hindering the development of more sustainable logistics practices.

Other future developments of this research could involve exploring potential solutions or strategies that offer a comprehensive view of the sustainability implications of applying AI to logistics, such as identifying specific KPIs and metrics that can be used to measure not only the sustainability impacts of logistics from a traditional perspective, but also the negative impacts of AI, such as the large amount of power used to run the algorithms and the other risks mentioned in chapter 2.1.1.

Lastly, it could be interesting to conduct a comparative analysis of how companies from different countries and industries approach the measurement of sustainability implications of AI solutions in logistics, to identify potential best practices and compare the status of the implementation of those solutions in different countries.

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