Leslie Joy Simpia

Machine Learning Adoption: The Interplay of Cost, Time, and Systems Integration

Machine Learning Business Applications in Logistics

Metropolia University of Applied Sciences

Metropolia Business School

International Business and Logistics

Bachelor's Thesis

30 April 2024

Abstract

Author:	Leslie Simpia
Title:	Machine Learning Business Applications in Logistics
Number of Pages:	50 pages + 3 appendices
Date:	30 April 2024
Degree:	Metropolia Business School
Degree Programme:	International Business and Logistics
Specialisation option:	Supply Chain Management
Supervisor:	Heikki Heponiemi, Senior Lecturer

The logistics sector, which has evolved from strategic military operations, is now shifting to a data-driven environment where the integration of digital and physical is crucial to remain competitive in the intricate sector while navigating disruptions in a dynamic global market. Ushered by further research, technological advancement and the proliferation of data, machine learning (ML) as a tool offers potential solutions in diverse industries with its strength in analysing massive data sets, providing quick actionable insights.

The study explores the necessary aspects of ML to understand its nature. ML applications across different sectors will be explored, emphasising the logistics sector. While most intelligent applications involve ML, many enterprises could still be at the crossroads of adopting the technology. Thus, this paper aims to provide a clearer understanding of the technology by providing fundamental business cases. Therefore, a qualitative method is conducted for this purpose.

This study highlights the necessary considerations for successful adoption, particularly emphasising time, cost and systems integration factors. ML applications have different facets; thus, it can be used to solve various problems. However, adopting machine learning also presents multifaceted challenges that could be overcome with strategic and proactive considerations. By implementing these recommendations, organisations can position themselves in the ML market, navigating the complexities of time, cost, and systems integration.

Keywords: ML, time management, cost efficiency, systems integration

Contents

List of Figures and Tables

Glossary

AI	Artificial Intelligence
IoT	Internet of Things
IR	Industrial Revolution
ML	Machine Learning
MLOps	Machine Learning Operations
SC	Supply Chain
TMS	Transportation Management System
WMS	Warehouse Management System

1 Introduction

The First Industrial Revolution marks a significant milestone in human history, characterised by the transition from human and animal labour to mechanised technologies. Mohajan (2019) highlighted innovations such as the steam engine, spinning jenny, and iron production techniques that revolutionised industrial processes. This period is renowned for its profound impact on global economic growth, leading to increased production and consumption among the general population. Advancements in transportation infrastructure, including canals, roads, and railways, eased the movement of goods and people, expanding markets into national borders (Mohajan 2019).

Today, the flow of information is as critical as the transportation of goods and people, and the rapid and seamless exchange of information emerges as a crucial determinant of competitive advantage and operational efficiency. Tech giants Amazon, Apple, and Microsoft are among the most valuable listed firms in the world, and data usage is considered the oil of the digital era (The Economist 2017). The era of digitalisation has ushered in a paradigm shift, facilitating streamlined connectivity and information dissemination through advanced technologies. Wiseri, Donthu, Mehbodniya, Vyas, Quiñonez-Choquecota, and Neware (2022) underscore machine mearning (ML) as a pivotal catalyst in the digital revolution, offering unparalleled efficacy in strengthening supply chain networks and enhancing operational efficiency in logistics.

This paper presents the literature surrounding machine learning and its potential benefits for the logistics sector. Additionally, it examines the fundamental concepts of machine learning and explores how its distinctive features can positively impact various operations, such as the logistics sector. The paper specifically aims to answer whether a company should adopt ML applications, weighing aspects of cost, time and system challenges.

2 Methodology

This study utilised a qualitative method, and interviews were conducted in April 2024. Ragin (2004:22) emphasised that effective qualitative research focuses on highlighting the features and strengths rather than on its shortcomings. The participants were given the questionnaire ahead of time, considering the complexity and vastness of the topic of ML. Kumar (2005) refers to the interview method as the best way to gather information on complex issues as it allows the participants to prepare beforehand. Moreover, Kumar (2005) added that interview quality can vary as each interview is different in addition to the interviewer's knowledge and skills.

The objective of this paper is to assist companies considering the adoption of ML solutions. Therefore, the interview was conducted from both business and technological perspectives to provide a holistic approach to adopting ML solutions, focusing on key considerations such as cost, time, and system integration. In addition, this study considered other significant factors that affected the company's adoption of ML solutions in its logistics operations. These open-ended questions (see Appendix 1 and 2) could provide further insight regarding ML adoption.

3 Machine Learning

3.1 Machine learning as a concept

Learning is a fundamental cognitive process in humans, wherein knowledge is acquired through exposure to various environments, including observation, experience, and education. In machine learning ML applications, computers utilise diverse forms of data, such as images and text, to analyse and identify patterns, enabling them to make predictions (Brown 2021). Mohri, Rostamizadeh, and Talwalkar (2018) emphasised the importance of continuous learning, referred to as being "experienced," where computers use newly added data to make accurate inferences. In the next section (see sub-Section 3.4), more detail will be discussed about this process, a critical component essential for enabling computers to effectively utilise current data and integrate additional data inputs, enhancing the accuracy of results.

Moreover, Soofi and Awan (2017) articulated that ML represents the convergence of various scientific disciplines, encompassing computer science, statistics, and engineering. Supported by rigorous scientific principles and its capacity for iterative learning, ML has the potential to yield reliable insights from data while continually improving its performance over time.

3.2 ML and AI

In today's era of technological advancement and automation, the terms "AI" and "ML" are frequently used interchangeably, reflecting their close relationship. This section of the paper seeks to clarify the concept of AI and its connection to ML by offering an overview of both fields.

Haidine, Salmam, Aqqal & Dahbi explain that AI is a science that enables machines to sense, comprehend, act and learn at a human-like intelligence level using different technologies (2021:48). This comprehensive integration of technologies enables machines to effectively act, think, and learn to solve an issue (Google Cloud 2023).

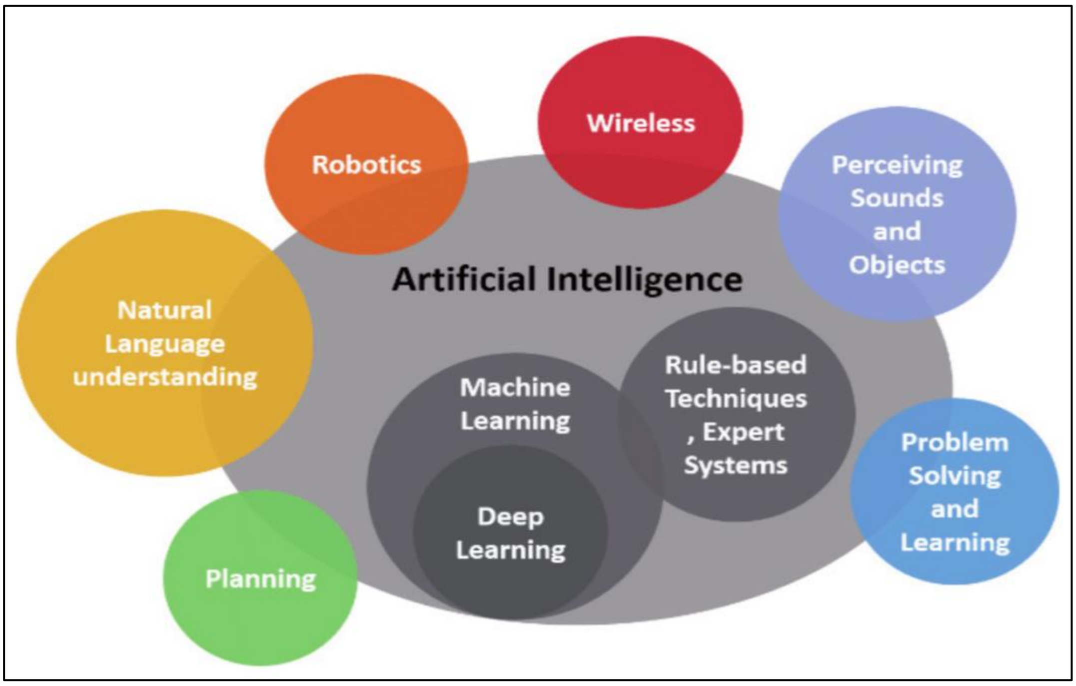

Figure 1 An overview of the huge field of AI (Haidine et al. 2021:49).

As Figure 1 from the previous page illustrates, the extensive field of AI encompasses a range of sub-disciplines, including machine learning and expert systems. Moreover, ML, portrayed as a subset of AI, highlights the core interrelationship between these domains, as evidenced by the interchangeable use of terminologies associated with them.

While AI encompasses a broader range of applications, ML represents a more specialized domain focused on enabling computers to learn in a manner comparable to humans (Haidine et al., 2021:49). However, despite its specificity, ML is fundamentally expansive due to its associations with various mathematical and scientific disciplines, including computer science, statistics, and engineering (Soofi & Awan 2017). As noted by Sharma & Kumar (2017), ML empowers computer systems to undertake intricate processes by learning directly from examples, data, and training experiences. On the basis of these definitions, it is evident that AI seeks to address a multitude of challenges. In contrast, ML is confined to performing a specific task it is programmed for, leveraging data to generate conclusions or predictions.

Furthermore, Alpaydin (2016) asserts that ML has emerged as the primary driving force behind AI, evidenced by the predominant focus on ML within AI publications. Additionally, Haidine et al. (2021:49) underscore ML as the most advanced technology within the AI realm, facilitating network operators' adaptation to higher service quality by enhancing operational intelligence and resource utilisation crucial for advancing next-generation mobile networks. Moreover, Kuntz and Wilson (2022) recognise AI and ML as significant pillars in the field of Chemistry, emphasizing their roles in achieving computational savings and enhancing accuracy in laboratory simulations (Pure and Applied Chemistry 2022). In transportation, AI and ML are trending concepts addressing future needs through market and capacity forecasting (Srivastava 2023).

These recent publications underscore the continuous integration of machine learning into artificial intelligence technology, driving advancements across diverse industries. Despite subtle differences in their scopes, AI and ML, considered together as a concept, are indispensable due to their interconnectedness.

3.3 Development of ML

The history of utilising computers as calculating devices spans over 60 years, with roots traced back to the pioneering work of mathematician and computer scientist Alan Turing in the 1950s (Mueller & Massaron 2016:12). Turing's contributions, including his work on cryptological warfare during World War II and his influential paper "Computing Machinery and Intelligence," are acknowledged as foundational to the development of modern computer science (Epstein, Robets, & Beber 2008:14).

However, before any form of computer deciphered codes or triumphed checker game, the groundwork for machine learning had already started in the early 1940s. Walter Pitts and Warren McCulloch laid the groundwork by developing the first mathematical model of neural networks, offering insights into brain functions (Norman 2024). Following this, Donald Hebb's work in 1949 further expounded the communication between neurons, forming a cornerstone for artificial networks (Foote 2021). These pioneering efforts paved the way for the development of functional systems in the 1950s.

Turing's efforts to explore machine intelligence paved the way for further advancements and formal recognition of the field. According to Cordeschi (2007), John McCarthy of the Massachusetts Institute of Technology (MIT) introduced the concept of AI building upon Turing's earlier work. Subsequently, machine learning emerged as a distinct field. Arthur Samuel introduced the term during his work on checkers, which explored the concept of machines solving problems without explicit programming (Wuest, Weimer, Irgens, & Thoben 2016).

Alan Turing's groundbreaking endeavours in creating intelligent machines and Arthur Samuel's achievement in crafting the first IBM computer program capable of learning from experience significantly influenced the progress of ML. This interplay between human intelligence and machine learning formed the bedrock of AI, with ML emerging as a subset of this domain (Haidine et al., 2021:48). The course of AI and ML development is related in various literatures (Coghill, 2023; Jones & Groom, 2019:2; Toosi Bottino, Sabou & Rahmin 2021), underscoring their intertwined evolution.

The advent of the Perceptron in 1957 by Frank Rosenblatt marked a significant milestone in ML, showcasing machines' capacity to learn through pattern recognition (Fradkov 2020). However, the 1970s to 1980s witnessed a decline in AI and ML investments, known as the "AI Winter," due to scepticism regarding neural network limitations (Forbes 2017). Nevertheless, dedicated researchers continued forging the path, leading to breakthroughs in the 1990s driven by enhanced computing power (Forbes 2017).

With better computational capacity, ML underwent a significant transformation, shifting from a knowledge-driven approach to one fuelled by data abundance (Marr 2016). This shift was exemplified by groundbreaking developments in ML applications. In 1997, IBM's Deep Blue defeated world chess champion Garry Kasparov in a rematch, showcasing its ability to analyse 200 million positions per second (Achenbach 1997). Notably, machines like Deep Blue demonstrated remarkable endurance, as they do not experience fatigue like humans, contributing to their consistent performance throughout the tournament. In 2011, IBM's Watson outperformed human champions in a quiz show using diverse algorithms, highlighting the versatility and sophistication of ML (De Jesus 2021). Simultaneously, Google's DeepMind developed AlphaGo, a deep neural network that mastered the intricate board game Go, surpassing human champions (De Jesus 2021). These advancements were simultaneous to notable progress in speech and facial recognition technologies. For instance, Amazon introduced Alexa, a voice-enabled device assistant, in 2011, revolutionising human-computer interactions (Santo 2019). Additionally, by

2014, visual recognition technology achieved human-like precision in identifying individuals in photographs, further expanding the horizons of ML applications (Foote 2021).

The choice of games like checkers and board games as testbeds for evaluating machine capabilities is rooted in their structured yet complex nature, providing an ideal platform for assessing decision-making abilities (Lu & Li 2022). ML applications span diverse sectors, from marketing and finance to transportation and healthcare, driven by the proliferation of big data, declining computing costs, and algorithmic advancements (Fradkov 2020 and Forbes 2018).

The future of ML appears promising, underpinned by exponential data growth and technological advancements. However, ethical concerns regarding human replacement in the workforce and challenges in deploying ML in business contexts persist (Chui, Manyika, & Miremadi, 2016; Lee & Shin, 2020). Moreover, managing vast amounts of data and developing robust algorithms pose ongoing challenges, necessitating human intervention to ensure meaningful outcomes (Wuest et al., 2016; Sharma & Kumar 2017).

While ML holds immense potential for innovation and societal impact, careful navigation of its implications is essential to harness its benefits responsibly. The interplay between human intelligence and machine learning promises continued evolution and transformative possibilities across various domains.

3.4 ML Process

Multiple authors have offered definitions of ML, shedding light on its multifaceted nature. According to Kashyap (2018), ML is a multidisciplinary field that enables computers to uncover significant insights and patterns from data. Mitchell (1997:421) underscores the complexity of this field, which draws from various disciplines such as statistics, computational complexity, neurobiology, and philosophy. Cady (2021:14) characterises ML as a mathematical technique that originated from computer science, driven by advancements in computational power and the availability of extensive datasets. These definitions collectively highlight ML's ability to navigate through intricate and large datasets, providing immediate insights that would otherwise be time-consuming to obtain. Backed by statistical principles, ML efficiently analyses data and predicts outcomes. This section adopts a simplified ML process, as shown, and further discussion will be provided.

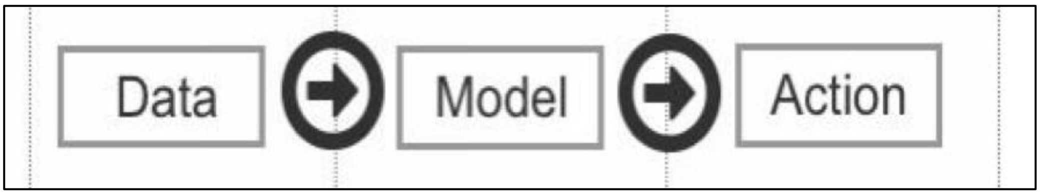

Figure 2 Machine Learning simplified process from Theobald (Theobald 2017).

Data is the foundational element in implementing machine learning as the initial step in the process, as depicted in Figure 2 above. While superficially perceived as mere numbers and text collected for practical purposes, the essence of data extends beyond quantifiable or qualifiable material. According to the University of York (n.d.), data encompasses any interpretable information, irrespective of its form or structure. In machine learning applications, data is categorized into two main types: and unlabelled. Labelled data includes the target characteristic or label within the dataset, whereas unlabelled data lacks such target labels (Serrano 2019). The distinction between these data types informs the selection of appropriate machine learning methods, a topic further elaborated in Chapter 3 (Types of ML). Serrano (2019) offers a real-life example to clarify these technical terms.

> Normally, if we are trying to predict a feature based on the others, that feature is the label. If we are trying to predict the type of pet we have (for example, cat or dog) based on information on that pet, then that is the label. If we are trying to predict if the pet is sick or healthy based on symptoms and other information, then that is the label. If we are trying to predict the age of the pet, then the age is the label. (Serrano 2019).

Essentially, differentiating data and information is fundamental for understanding the importance of the outputs generated by the ML process.

Shen (2020) articulates that data is a fact that can be collected and stored in different formats for processing. Information, on the other hand, requires programming and design to derive value and leverage data. While both can represent facts to some extent, the critical difference is enhancing utility by going through a process using algorithms.

Model, the second stage in the process as illustrated in Figure 2, involves applications of algorithms. According to Stone (1971:4), an algorithm can be broadly defined as "a set of rules that precisely define a sequence of operation". To illustrate, consider a recipe for cooking spaghetti. While there may be variations in the method, the fundamental steps remain consistent; thus, the properties of definiteness and finiteness take part. Stone (1971:8) refined the previous definition, asserting that an algorithm comprises effective and specific rules that ensure termination within a finite time frame. Machine learning utilizes a structured set of programming instructions delineating clear steps for a computer to execute. Compliance with these instructions guarantees a predictable outcome, culminating in completing the task within a defined time frame.

Following the collection of data and the selection of appropriate algorithms tailored to address the problem, the training phase commences, wherein input data, also known as training data, is fed into the algorithms. This process aims to uncover patterns or rules within the data, thereby facilitating the development of models capable of classification or prediction (TechTarget 2023). Subsequently, as explained by Theobald (2017), once an accurate model is established through an evaluation conducted by experts, a second set of data, referred to as test data, is subjected to the model, yielding an actionable output, which the author referred to the third stage as the Action Drawing an analogy to the preparation of spaghetti, where ingredients represent data and cooking steps symbolize algorithms, the introduction of additional elements such as tuna or meat results in variations like tuna spaghetti or spaghetti Bolognese. Similarly, in machine learning, ML model variations emerge as outcomes of algorithmic processes (Amann 2021).

While Theobald's book, "Machine Learning For Absolute Beginners," necessitated a certain level of computer programming proficiency to grasp intricate mathematical operations, the simplified model explained the essence of the ML process. It emphasised the nature of supplying data to a computer, enabling it to comprehend the underlying patterns using algorithms, ultimately constructing models that enhance performance by accumulating additional data. This iterative process mirrors how individuals learn through exposure to their environment and prior experiential knowledge.

4 ML Types and Applications

It has been previously established that a computer can help us solve problems by adhering to programmed instructions or algorithms to accomplish a task. One may understandably question the necessity for employing multiple algorithms or ponder whether a superior alternative exists. This inquiry seeks to delve into the rationale behind such considerations. Generally, the fruitfulness and the efficiency of an ML solution depend on the nature and characteristics of data and the performance of the learning algorithms.

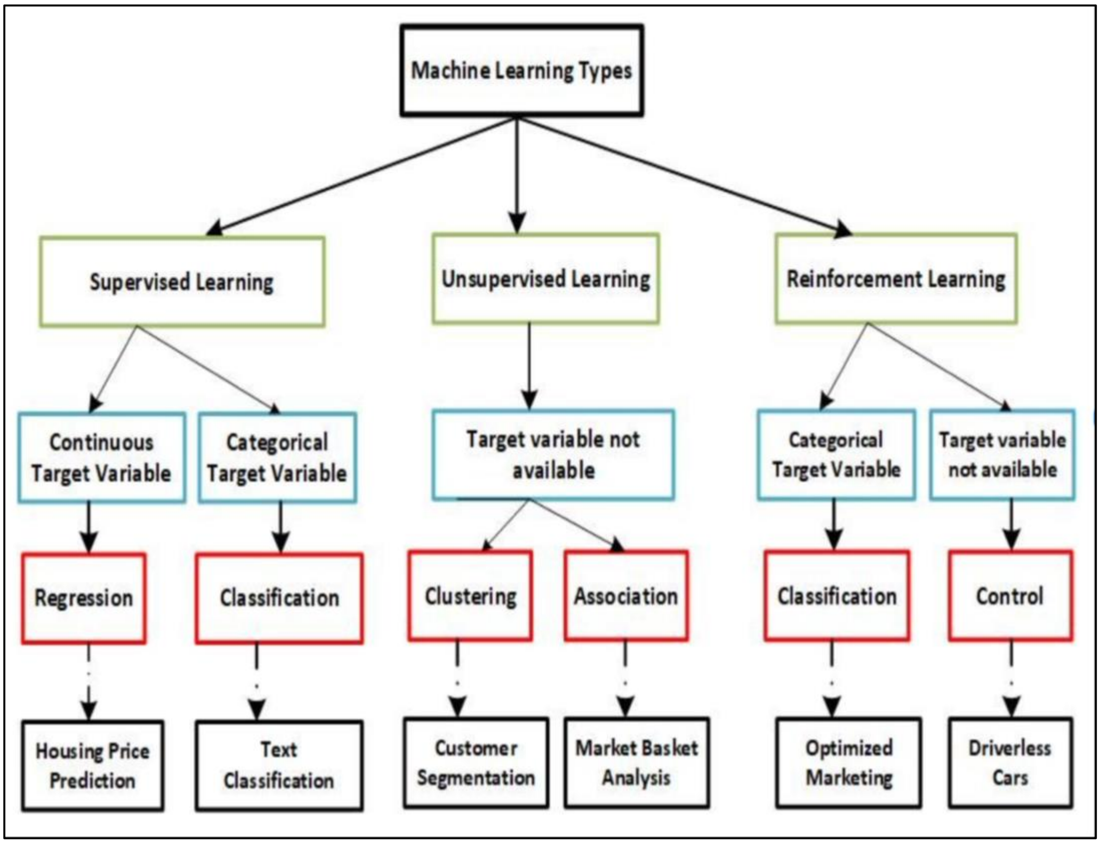

Figure 3 Major Machine Learning Types Dike, Zhou, Deveerasetty, and Wu 2018).

The preceding page's image shows several algorithms divided into three main categories for machine learning: The writers summarised supervised, unsupervised, and reinforcement learning using typical commercial applications like price prediction. Each technique has distinct classifications, as shown in Figure 3 on the preceding page, which are discussed in the following section of this study.

4.1 Supervised learning

Image recognition, text processing, and recommendation systems are some forms of supervised learning that are the most common applications today (Serrano 2019). Supervised learning, as denoted by the term, relies on labelled output, wherein the input dataset is accompanied by the expected output during the training phase (Bonaccorso 2018:9). This explicit guidance from the correct output enables the training of models to produce the desired output and refine their performance iteratively over time, thus introducing a level of automation (IBM n.d.).

Supervised learning algorithms typically generate models that fall into two categories: regression and classification models. The primary distinction between these lies in the nature of their output. Classification models are employed when the aim is to predict discrete values, such as categorising animal types based on images. Conversely, regression models are utilised for forecasting continuous values, like predicting an animal's weight based on age, as clarified by Serrano (2019). However, the development of accurate models in such machine learning endeavours, which often necessitate large datasets for iteration, is not without challenges. IBM (n.d.) underscores issues such as data inaccuracies and the time-consuming nature of training, which should be taken into account to facilitate the creation of lasting learning models.

4.2 Unsupervised learning

Unsupervised learning represents another common type of machine learning methodology, distinguished from supervised learning by the absence of labelled data. In unsupervised learning, training aims to conceal patterns within datasets and generate labels through unsupervised algorithms (Theobald 2017). These algorithms, typically categorised as clustering or regression, are instrumental in instructing machines on grouping elements based on their similarities (Bonaccorso 2018:181).

Unsupervised algorithms, categorised as clustering or regression, help understand and group datasets according to their similarity. Bonaccorso (2018:181) suggests that clustering helps understand the dataset comprehensively, while association expands attributes to neighbouring data points, assuming similarity extends beyond specific features. A widely used application of unsupervised learning is market basket analysis; it seeks to identify connections between objects, like those seen in grocery shops.

Customer segmentation using unsupervised algorithms proves particularly valuable in scenarios characterised by a large customer base and extensive data (Ozan 2018). However, concerns regarding the accuracy of machine learning models arise in the absence of labelled data, as highlighted by Sharma and Kumar (2017), that without labelled data for validation, verifying the structural accuracy of models becomes challenging. Nevertheless, segmenting a vast consumer base into discrete groups based on patterns identified through algorithmic processes holds the potential to identify niche consumer segments. This, in turn, facilitates the development of customised goods and services tailored to specific consumer preferences, ultimately enhancing the profitability of businesses.

4.3 Reinforcement learning

Unlike supervised and unsupervised learning, reinforcement learning operates without explicit data to solve problems (Serrano 2019). At the same time, typical ML methods rely on predefined datasets, reinforcement learning leverages observations from a reward-punishment paradigm to guide algorithms in processing data (Mohammed, Khan, & Bashier 2017). To illustrate this concept, Theobald (2017) relates reinforcement learning to playing a video game, where the player's character learns from experience in the virtual environment, adjusting behaviour based on outcomes to improve performance. Typical applications of reinforcement learning include game-solving, autonomous robot control, and stock trade analysis based on feedback signals, as Bonaccorso (2018:14) stated.

The answers to deciding which algorithm to use lie in several factors, such as data size, quality, business need, and available time, as mentioned by Wakefield (n.d.). Moreover, Cady (2021:2) stressed the importance of incorporating human judgement in making algorithmic rules, measuring their effectiveness and constant monitoring.

5 ML in Logistics

5.1 The shift to data-driven logistics

Long before logistics was involved in the modern sense of obtaining, moving, and storing products, it used to be a military art of moving men, equipment, and animals in war (Cowen 2014:25). The author further credited the success of Roman and Greek empires due to the efficient movement of troops sustaining campaigns.

In the modern era, logistics as we know it didn't fully emerge until the First Industrial Revolution (1IR). According to Mahajan (2017), the invention of the steam engine shifted manual labour to machinery together, and the development of rail and roads paved the way for the global economic surge. The development of machines eased production, making the goods accessible to common people and eventually opening the trade across borders. The global landscape underwent a profound transformation catalysed by the advent of aircraft and automobiles during the Second Industrial Revolution (2IR), as noted by Chan (2019). These groundbreaking innovations revolutionised transportation, expanding the reach of mobility not only for individuals but also for the international trade network. Over time, the increased accessibility and economic viability of these modes of transport fundamentally reshaped global commerce and connectivity, ushering in an era of unprecedented exchange and interdependence. The subsequent Third Industrial Revolution paved the way for the birth of electronics. Chan (2019) features the pivotal role of this revolution in reshaping human interaction with technology and driving unprecedented levels of connectivity and efficiency.

Building upon the foundations laid by the earlier industrial revolutions, Manners-Bell and Lyon defined the Fourth Revolution (4IR) today as the concept of combining digital, physical, and organisational innovations (2019:15). This conceptual framework prompts an inquiry into the enduring nature of globalisation, particularly underscored by the disruptions witnessed during the Covid-19 pandemic, where international commerce faced significant constraints due to border closures. However, White (2023) contends that the world remains interdependent as the world is highly dependent on flows. "Today is the Suez Canal, yesterday was the pandemic and tomorrow is hurricanes." Steer and Dempsey (2021) quoted Shehrina Kamal, citing that black swans may disrupt global trade but will not put it to a halt. While companies try to prepare for future strains, the author furthers that the unprecedented, such as the canal blockage, encouraged companies to diversify and adapt their strategies accordingly. While disruptions are inevitable, proactive actions are vital. Furthermore, disruptions serve as opportunities for uncovering weaknesses, enabling coordination to evolve into a more resilient and robust structure.

The evolution of logistics, from the era of steam engines and international connectivity to the integration of digital and physical innovations, illustrates a historical journey by embracing innovation and exploration, ushering in a new era of commerce. Additionally, continuous technological advancement, infrastructure development, geopolitical shifts, and other complex factors are pivotal in shaping the future evolution of logistics.

6 ML applications in Logistics

Harrison and van Hoek (2011:7) define logistics as coordinating material and information across the supply chain to meet customers' demands. The author furthers that the goal is a synchronised flow of materials from production to delivery and the reverse flow of information from the customer to the manufacturer. However, Rushton, Croucher and Baker (2022:4) argue that logistics has no accurate definition, as every industry can have different coverage, such as product and strategy. Moreover, Rushton et al. (2022:5) highlight that the process entails information flow and storage in addition to the activities involved in moving the product from production to distribution. The definitions above correspond to logistics' paramount role in moving goods across the supply chain.

Logistics is a complex process involving various operations, from placing an order to delivering a product. Langley (2019) mentioned that for a product to be delivered, about 50-70% of activities are outsourced by third-party providers, known as logistics service providers (LSP). It is a significant portion of the coordination to ensure successful order fulfilment. Waters and Rinsler claim that for logistics to realise full benefits, links should be extended and closely coordinated to the whole supply chain, minimising costs and fulfilling in the shortest time, contributing to a maximum profit (2014:3). Furthermore, the seamless transmission of data across the process is fundamental to optimising logistical processes, thereby ensuring that consumer needs are met with efficiency and precision.

Rushton et al. (2020:4) categorised the three main processes in logistics as transportation, inventory, and warehousing. While these encompass various activities, this paper will focus on key concepts in the consecutive section discussing the applications of ML in logistics.

6.1 Transportation

As involved in separate activities of production, manufacturing, delivery and returns, consuming one-third of the logistics costs and systems makes transportation a critical element, as Tseng, Yue and Taylor (2005) mentioned. During the research, it was found that ML applications have been utilised for different purposes within transportation. Zantalis, Koulouras, Karabetos & Kandris (2019), in their review of smart transportation, mentioned that the data of users with their specific locations, ML estimates optimal routes, minimising travel time and reducing energy and emission consumption. ML algorithms also detect potholes, cracks, speed bumps and other road anomalies acquired from smartphones (Silva, Shah, Soares, and Rodrigues 2018). However, the author notes the importance of the iteration process as anomaly accuracy tends to decrease compared to controlled conditions. Although technology alone cannot entirely eliminate road injuries and accidents, it can significantly enhance truck drivers' situational awareness. This improvement allows them to perceive their surroundings better, reducing the risk to people's lives and mitigating the financial costs associated with accidents (AJOT 2020).

In 2023, China, Asia, and Europe emerged as the leading eCommerce markets, with projected annual growth (Statista 2019). The recent surge in online shopping has revolutionised the retail landscape, offering unparalleled convenience and contactless transactions that appeal to consumers worldwide. This exponential growth, coupled with the expansion of urban populations, has intensified the demand for goods and services, prompting a competitive push for flexible and efficient delivery solutions (Bruni, Fadda, Fedorov, & Perboli 2023). However, this growth presents challenges, particularly in intermodal transportation, which facilitates seamless movement across various modes of transport in a single journey (Sing, Wiktorsson, & Hauge 2020). Gocmen and Erol (2019) have focused on addressing train loading issues within intermodal transport, demonstrating promising results by implementing machine learning algorithms. Furthermore, overcoming the last-mile delivery challenge, the final phase of transporting products to customers' doorsteps, is critical for eCommerce operations. Zantalis et al. (2019) suggested combining various information services, such as Google Maps and crowd-sourced data, to enhance navigation accuracy during this crucial delivery stage. Furthermore, a leading logistics company mentioned that it strategically leverages data to improve transparency and facilitate informed decision-making processes. It offers logistics stakeholders a structured, refined, and intelligible real-time condition within logistics centres or during transit (Jeske, Grüner, and Weiß 2020). As brick-and-mortar retail and eCommerce continue to evolve, ensuring customer satisfaction in the ever-expanding digital marketplace is paramount.

ML in transportation presents different solutions for essential activities in shipping and delivery. Efficient movement and optimised information flows are the highlights of ML in transportation, particularly evident in route optimisation and in providing real-time visibility conditions. On the other hand, accuracy might vary, especially in controlled setups during the iteration phase; thus, keeping an eye on the continual machine learning process is essential.

6.2 Inventory

Ultimately, logistics is the complex process of moving goods inventories effectively throughout the supply chain to satisfy customer needs. Thus, strategic allocation of stocks within the network is paramount. Rushton et al. (20222:220-222) mentioned some purposes, such as cycle stock for the average demand, safety stocks to cover fluctuations in demand and seasonal stock to allow expected increases in demand, such as Christmas.

Demand forecasting is anticipating product or service demand under unpredictable and competitive forces. Praveen, Prateek, Pradyumna, Pragathi and Madhuri (2020) used different sets of algorithms. The authors discovered that the kind of datasets (structured or unstructured) produces different results and could perform better with the suitable algorithm. Moreover, they highly recommend demand forecasting for small/medium enterprises to maintain inventory and minimise manual labour for profitability. Amazon's ascendancy in eCommerce is known for its personalisation services, which store global customer data in their database. Usage patterns and search history data help ML to learn and recommend products to meet forecast demand, which would be difficult if manual employees had to deal with enormous data (GeekforGeeks 2023). Moreover, the ML features enabling pattern recognition are relevant to demand forecasting without human involvement (Akbari and Do 2020).

6.3 Warehousing

Warehousing types can vary within the chain depending on factors such as its function, product type and ownership (Rushton et al., 2022:271). Moreover, the author furthers that its main objective is to facilitate the storage and movement of goods throughout the chain to the end customer. Over the past decade of technological advancements, the warehouse's role has also changed from a storage perspective to a critical point of matching supply and demand through inventory management to meet the customers' demands (Tiwari 2023). This means that warehouses are crucial in ensuring product availability when customers want them. This shift could be argued as one of the catalysts in the need to shift into smart warehouses. Industry 4.0, another term for smart warehouses, is the adoption of IoT, blockchain, big data analytics, artificial intelligence, machine learning, deep learning, and robotics with the potential to transform warehouse operations (Tiwari 2023).

Yu, Liao, Li and Liu (2019) conducted a simulation infusing two algorithms based on ant colony and reproduction algorithms to automate the picking path of the tool for lifting and moving pallets (stacker), reducing time and improving efficiency. Zadgaonkar and Chandak (2021) used a beacon with an ML application to minimise the time needed to locate raw material inside the warehouse from 11 minutes to 2.2 minutes with high accuracy compared to other algorithms. While the speed time is impressive, the author also mentioned that the algorithm was tested in a dense and sparse warehouse; therefore, further work is needed to cater to different warehouses. Tufano, Accorsi and Mazini (2021) explored the utilization of ML for predicting warehouse design, specifically for assigning incoming SKUs to existing storage systems, thereby enhancing efficiency for third-party logistics (3PL) providers by organizing and managing products based on size and type even before storage takes place.

7 Considerations in Adoption

The preceding sections have explored the move of the global logistics landscape towards digitalisation as technology becomes increasingly advanced. AI and ML are transforming logistics into a data-driven field capable of optimising delivery routes in real-time, forecasting inventory needs, and automating customer service interactions (Krishnan et al., 2024). These current adoptions of ML technology has proven advantageous in offering competitive advantages.

Logistics has long been dynamic, initially rooted in military strategy, and now, it is navigating the interplay between digital advancement and the physical realities of the global market. As witnessed during a pandemic and geopolitical issues, the current economic challenges put logistics operations to the test regarding handling risks and disruptions, highlighting the need for agility and resilience in adapting to unforeseen circumstances. Krishnan, Perumal, Govindaraj, and Logasakthi (2024) asserted today's role of digital technologies such as the Internet of Things (IoT), blockchain and AI in enabling more efficient and transparent operations. Mohamed-Iliasse, Loubna, and Abdelaziz (2020) asserted the greater importance of integrating digital technologies than cost reduction or addressing company challenges to gain immediate insights into evolving market expectations. Moreover, this section will discuss the interplay of cost, time and systems integration considered as critical factors to provide a holistic view of challenges and oppurtunities in ML adoption.

7.1 Integration with existing systems

AIMagazine, a platform that connects the world's largest AI brands, curated a list of top ML companies based on their significant contributions in 2023. Notable names included Amazon Web Services (AWS), Microsoft, Google, IBM, SAS, and Databricks (Jackson 2024). These prominent third-party providers offer an end-to-end solution known as a “cloud” computing platform where applications and files are hosted, making all activities web-based instead of desktop-based (Mirashe and Kalyankar 2010).

Data is integral in any application as the foundational aspect of ML requires considerable data to train before creating a model. Azure, Microsoft's ML cloud platform, provides various services such as "servers, storage, databases, networking, software, analytics, and intelligence (Microsoft Azure n.d.). DHL, a global leader in logistics, adopted the Resilience360 software provided by AWS as a risk management solutions platform. DeNittis (2023) elaborated on how the company leverages ML systems by gathering data through numerous sensors, which are then centralised into WMS (warehouse management system) and TMS (transportation management system). The author furthered that DHL states the compatibility of the software to most WMS and other IT infrastructure. Moreover, successful integration with other systems, such as WMS, becomes essential for automating ML solutions later, especially when operational systems are integral parts of the data and infrastructure (Krushe-Lehtonen and Hofmann, 2020). Moreover, adopting technologies aligning with the current systems prevents technological obsolescence and associated expenses (Adekunle and Ruth 2023).

While large corporations like DHL may have the resources to access comprehensive AWS solutions to reduce costs and process automation, the same may not apply to smaller companies. Smaller businesses may not require end-to-end solutions and may prioritise other aspects of their operations. A 2020 survey on ML State Enterprise conducted by Algorithmia (2020:6), the largest marketplace for algorithms in the world acknowledged by Forbes, shows that for smaller companies with 100 employees or less, ML-used cases focus on generating customer insights and improving customer experience. Therefore, the complex integration of systems may not necessarily be a priority if a straightforward approach is enough.

Fagella (2018) suggests that smaller companies seeking to solve specific problems should look for AI/ML vendor companies that offer software and data science talent for small business implementation. Moreover, large solution providers such as Microsoft Azure also have cloud solutions for small to medium businesses, providing support and step-by-step guidance in building secure and scalable solutions for their specific ML applications (Microsoft Azure, n.d.). An out-of-the-box solution, such as Google Maps, Facebook ads, and virtual assistants, is prescribed by Fagella (2018) and will not require data professionals, IT infrastructure, or venture capital. Moreover, Monstarlab is a leading global consultancy specialising in end-to-end digital solutions for enterprises, highlights the inclusion of setting an approach where defined business targets are supported by a data strategy that will enable a functional system and delivery of desired outcomes (Kongsbak and Morville n.d.).

While big companies have increasingly adopted ML, its application in smaller enterprises is still a struggle. Moreover, Algorithmia (2020:23) encourages that the company's size is not in the pinnacle ML maturity stage. The report also argues that its findings on the growing use of ML in routine tasks will lead to more streamlined workflows. If the trend of more prominent companies developing solutions that are more accessible to smaller companies continues, this could help commoditise ML solutions, resembling breakthroughs from earlier IRs.

7.2 Time

The survey of more than 700 enterprises conducted by Algorithmia (2020:2) uncovered a rise in companies venturing into ML development. Yet, challenges in ML deployment and integrated applications prevent these companies from fully leveraging their ML investments. ML workflow, which consists of training data, model training and model deployment consisting of (Cong, Luo, Jian, Zhu, and Zhang (2022), is an extensive and lengthy process (Shashkina 2024). Deploying a single model alone takes at least or more than a month for 50% of the respondents, and 18% take longer than 90 days (Algorithmia 2020:2). This is attributed to the deployment stage, where a model is trained, tuned, and evaluated before it is put into production, where actionable business insights are created and formed (AWS Documentation n.d.).

ML Operations (MLOps), as illustrated in Figure 4 below, is a comprehensive framework for integrating ML workflow into production, where a continuous flow of data, training, modelling, and performance checks are run through in a cycle (Ritz, Phan, Sedlmeier, and Altmann 2022). Algorithmia (2020) mentioned that a year is necessary for production for some companies.

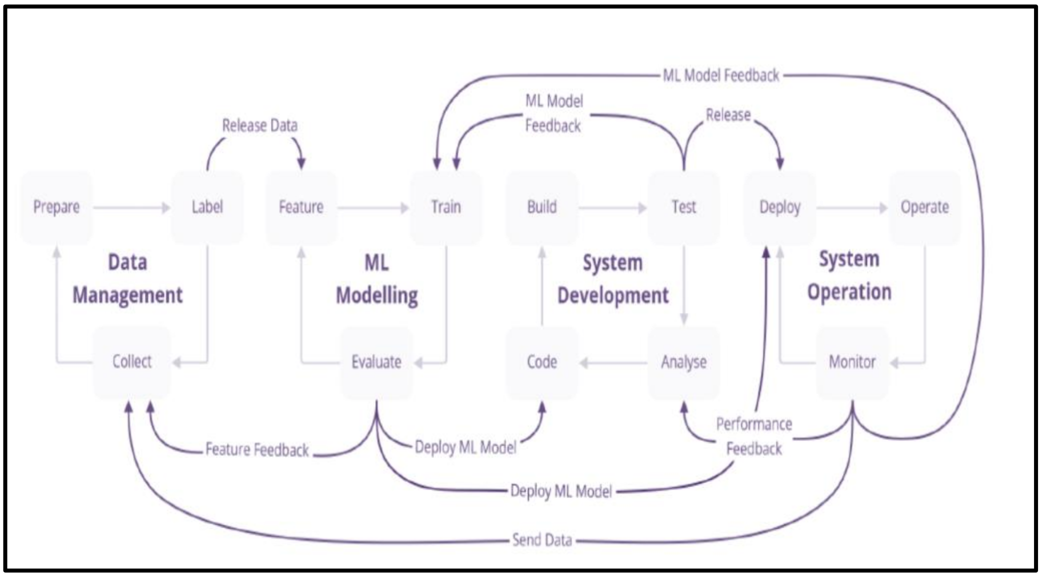

Figure 4 Integrated Machine Learning Operations (MLOps) (Ritz et al., 2022).

The depicted figure highlights that MLOps involves a continuous and iterative process, making collaboration paramount. Although the process demands significant time investment, MLOps aims to automate, offer end-to-end visibility, and facilitate rapid feedback, ensuring performance while ultimately saving time (Ritz et al., 2022). Moreover, the involvement of monitoring stages and performance checks in MLOps underscores the necessity of overseeing the whole process, even if automation is enforced.

For the majority of enterprises, AI and ML adoption tends to be slower and more costly than anticipated (Algorithmia 2020:15). Amazon's rise to dominance from selling books in today's global influence in e-commerce and logistics is attributed by Kruhse-Lehtonen & Hofmann (2020) to their understanding of the value of data, building human capacity together with the continuous internal technological transformation offering optimal services for customers. However, this is not the case for the 92% of companies in Algorithmia's survey lacking revolutionary maturity in their ML adaptation (2020:8). The relatively low number of companies effectively implementing sophisticated digital landscape could be attributed to the meagre information regarding the time frame of deploying ML solutions. Moreover, navigating the transition from traditional IT systems and operations to the digital domain, as noted by Kruhse-Lehtonen & Hofmann (2020), is a time-consuming endeavour. Nonetheless, there is potential for the accelerated deployment of models in production. Gartner's survey indicates a rise in the commercialisation of AI and ML technologies, which could facilitate faster deployment, enabling more enterprises to derive value from their technological ventures (Moore 2019).

7.3 Cost

In addition to having digitally skilled employees, Cichosz, Wallenburg and Knemeyer (2020) highlighted in their review of LSPs that one obstacle to digital transformation is finances. Regardless of the investment scale, associated costs are always essential for a business to continue innovating. Brown (2021) cited the 2020 Deloitte survey, where 67% of the respondents currently use ML, and 97% plan to continue in the following year. This aligns with the projected ML global market from $7.3 billion in 2020 to more than $30 billion in the next four years (Columbus 2020). American companies Google and IBM's early investment in developing AI and ML fields through computational board games is now accompanied by several countries investing in AI research and technology. While the US still leads the way with 60% of AI investments with $249 billion in private funding, the UK, China, Israel, Canada, and France follow closely behind (Keary 2024). As the recognised value of data increases, it shapes a data-driven ecosystem where data is embedded in every interaction and operation (McKinsey 2022). This trend shows that ML, among other AI technologies, is still developing and is yet to be embraced by the rest of the world. Moreover, as leading countries and large corporations investing in data-driven trends continue, we may witness increased usage and make the product more accessible to many enterprises, as seen during the last IRs.

During the research, it was observed that companies do not explicitly disclose numbers. On the other hand, major tech solution providers such as Amazon offer a flexible pricing scheme based on a company's needs, considering factors such as location, data storage, and processing requirements (AWS, n.d.). While this approach can provide companies with insights into potential investment costs, understanding technical terms to utilise a pricing calculator can be challenging. The field is inherently complex as ML encompasses various fields, such as statistics and computational complexity (Mitchell, 1997:421). Moreover, significant companies offer dedicated pages demonstrating how to begin with ML operations, including tutorials; thus, understanding the ML process remains pivotal.

ITRex Group, a software development firm specialising in helping enterprises integrate emerging technologies, estimates that the cost of ML development can range from $10,000 to $1,000,000 for a customised solution (Shaskina 2024), as shown in Figure 5 on the next page. Additionally, a comparison is made between the sample and a machine learning operation (MLOps), which refers to a collection of techniques and tools for deploying machine learning models (Symeonidis, Nerantzis, Kazakis, and Papakostas, 2022)

Operational Costs of a Machine Learning Solution				
	Bare-bones		MLOps Framework	
Model Infrastructure	*A single machine in the cloud with no load management*	***$9,000 / yr***	*Redundant machines with a load balancer, or Kubernetes-type cluster*	***$8,000 / yr***
Data Support	*Timed script executed on infrastructure to pull data*	***$6,750 (labor)***	*Independent data pipeline manager for continuous updates of analytic data*	***$10,000 (labor) + $3,200 / yr***
Engineering / Deployment	*Model copied from data scientists machine to cloud machine*	***$9,000 (labor)***	*Continuous integration and continuous deployment (CI/CD) system to pull model from registry*	***$24,500 (labor) + $516 / yr***
Total Investment	$15,750 (labor) + $9,000 / yr		$34,500 (labor) + $12,000 / yr	
5 year TCO	**$60,750**		**$94,500**	

Figure 5 Price estimate based on AWS infrastructure and third-party engineering for deployment support (Shaskina 2024).

The two approaches depicted in the figure above are a bare-bones approach with a lower price and a framework operations approach with a higher one. While the cost of ownership of the bare-bone approach costs less, it will lack the feature of automation and scalable systems, compared to MLOps, which is built with a crucial system to handle changes such as adding ML models (Coop 2021). While the previous estimation appears cheaper, a price structure by FINMODELSLAB appears more realistic and comprehensive. The estimate includes research, developing and maintaining IT infrastructure, marketing, and other overhead costs related to a successful operation, ranging from $ 405,000 to nearly $3,000,000 (Ryzhkov 2023). Considering the substantial investment, the author emphasises conducting detailed research to mitigate risk and achieve their objectives and growth. In addition, Kruhse-Lehtonen and Hofmann (2020) brought up the importance of prioritising the centralised budget required to scale up AI and data initiatives.

Cong et al. (2022) identified similar operational costs in their review of data pricing in ML pipelines. The authors explained that these pipelines serve as a collaborative link among numerous parties across multiple stages, each incurring associated costs. The steps and pricing tasks related to ML pipelines are illustrated in Figure 4 on the following page (Cong et al., 2022).

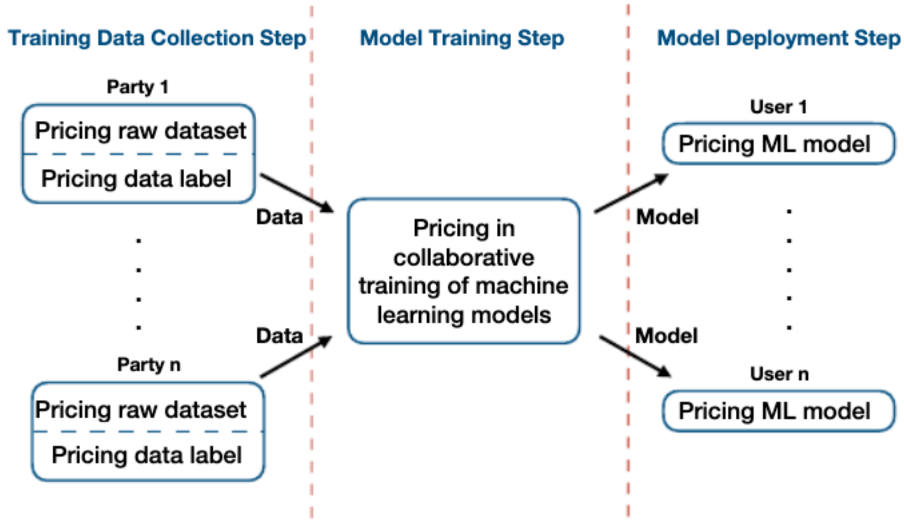

Figure 6 ML pipeline and pricing activities involved (Cong et al., 2022).

The main steps in Figure 6 above are training data, model training, and model deployment. Under each corresponding main step, different activities are identified where pricing is involved. Paleyes, Urma and Lawrence (2022) conducted a survey of case studies deploying ML cited by Ashmore, Calinescu and Paterson (2021), the four steps of ML workflow: data management, model learning, model verification and model deployment. While both reviews examine the process and pricing involved in deploying ML solutions, specific costs were not provided. Instead, the authors delved into a more detailed discussion of the process, which could impact the variable costs associated with deploying ML solutions. Cong et al. (2022) concluded that data pricing is still in the early years, and Paleyes et al. (2022) advocated a future academic on the pragmatic deployment of ML production. These studies highlight the intricacies of the ML deployment process that have not been fully understood. Furthermore, the identified activities could contribute to variable costs; thus, fixed pricing information may not be readily available.

For smaller companies still intimidated by ML, Itrex Group recommends starting with a basic product, conserving resources and allowing for flexible adjustments, making it easier to evaluate whether ML solutions are practical and feasible (Shashkina 2024). A company can hire certain data scientists who can rely on pre-packaged tools with models primarily focusing on defining the problem they seek to solve and evaluating if it aligns with the business case (Cady 2021:14).

These could help small-scale enterprises navigate a dynamic and innovative marketplace and develop critical solutions while sustaining operations. There is no shortcut in the reality of business. Large corporations such as Apple and Google also started somewhere, but one common denominator in success is positioning themselves before technological shifts (Kruhse-Lehtonen & Hofmann 2020).

8 Organisational implication

According to Kruhse-Lehtonen and Hofmann (2020), many data-driven organisations suffer from organisational disconnect. Symeonidis et al. (2022) added that even companies with sophisticated systems are frequently hindered during adoption. Thus, ML as a tool for developing business processes and creating value should be emphasised among decision-makers.

De Muynck (2023) referred to AI as "augmented reality," which aids humans in being more productive by accomplishing tasks on time with better output. An IT team and business functions working together are vital in aligning goals and resources, especially in data management (Kruhse-Lehtonen & Hofmann 2020). Moreover, Cong et al. (2022) highlighted the need for cooperation across all stakeholders at every stage for ML to be fruitful. Furthermore, Adekunle and Ruth (2023) asserted that coordination among stakeholders and processes enables seamless operation, reducing risks of technological conflict.

While many giant firms benefit from their advanced infrastructure, such as DHL, as previously mentioned, many companies are still not reaping the full advantage. De Muynck (2023) indicates that large companies' missing out on digital transformation is attributed to shifts in attitude and behaviour. Ultimately, Kruhse-Lehtonen and Hofmann (2020) mention that tight cooperation between data and business functions driving leadership and establishing a joint roadmap ensures a tangible and long-lasting outcome.

9 Interviews

Interviews with technology and business experts were done to offer a comprehensive strategy for implementing ML solutions, emphasising essential factors of system integration, cost, and time.

9.1 Business application point of view

Viola Elenius has been with Wolt Market for four years, a daughter company of Wolt, and currently serves as the Operations Manager. The interviewee has been closely involved in the company's development and primarily overseeing the physical setups of their grocery stores and warehouses. Founded in 2014, Wolt began in Helsinki as a tech company providing a food delivery platform, which has since scaled to include its courier apps and backend logistics (Wolt n.d.). Viola's firsthand experience from the company's journey underscores her credibility and expertise in the field. However, it is important to acknowledge limitations due to the technical aspects of the subject and functions outside Viola's responsibilities.

The first question asked about using ML applications in the company's operations. Viola mentioned that ML algorithms are mainly used to predict and forecast. In their specific use cases, algorithms are employed to predict the number of couriers needed at a given time; this is especially important when prediction algorithms consider other data, such as weather forecasts and important dates, which could affect their delivery efficiency. Forecasting the number of deliveries they will have is another critical case in allocating resources as they also work in partnership with their couriers. The company use their app, which has the workflow of receiving orders> store collects and prepares> courier picks up the order and customer delivery.

Systems Integration. Having their own app streamlines data collection from customers and employees, stores, and couriers, leaving a trail of interactions that can be utilised for actionable insights. Additionally, systems within the stores gather data for operational purposes, such as determining the optimal product capacity for a given space. This collected information allows for analysis of operational implications when making changes. The respondent furthers that from the process point of view, it is complex for a human to navigate manually in addition to the ongoing tasks. Moreover, Viola justified that "having data to read on and do something about it based on the given information, it is not quasi-ML but more on data analytics". Furthermore, the company's effort to gather more data is to map how each thing would relate to each other, resulting in a better and immediate understanding of the whole operation and ultimately better-serving partners and customers.

Viola states that Wolt started with one call for food delivery. However, with Wolt's immediate scaling came the challenge of maintaining consistency in their services, and as the complexity grew, the need for an automated process became imperative. Machine learning is employed when orders are received, with algorithms predicting courier arrival times and allowing Wolt's operations to adjust accordingly. The increase in data from using the company's application left a digital imprint on every activity. The data generated through these interactions enables the company to ensure successful product delivery or provide customers with real-time updates, such as the unavailability of an item from their order list. Finally, Viola emphasises the significance of data containing this information for the operational aspect, particularly regarding cost-benefit analysis, connecting dots about trends and finding root causes. On the other hand, Wolt still uses manual processes but rarely employs them as they are time-consuming and prone to more errors.

Time. As Wolt is a tech company with physical operations, Viola stated the importance of setting quarterly and annual goals, similar to any other company. Frequent road mapping is essential to make sure everything progresses quickly. Furthermore, their rapid expansion into two countries within two years was challenging. Viola reflected on the lessons learned during their technological journey, emphasising that implementing new systems or solutions becomes more complex as the company grows. The interviewee stated, "The earlier you adopt something, the easier it becomes because there are not many complex systems that must be integrated".

Cost. While Viola is not at liberty to disclose any cost information, the respondent emphasised the importance of conducting a Cost and Benefit analysis. It is worth pursuing if it demonstrates a net positive within the considerable timeframe. Moreover, she attributed the universal systems across their different country operations to cost-efficiency where any investments benefit all, immediately discarding the cost to its potential benefit. With this perspective, Wolt's leaders constantly work to seek funding, believing it will help the many countries, Viola expressed.

Further insights: Wolt began its operations in 2014 as a start-up in Helsinki, Finland. Viola narrated that their first order came from a phone call; ten years later, they operate in nearly 30 countries. When asked about Wolt's relatively immediate expansion, Viola stated they have two reasons for growth: "dealing with growth and enabling growth". The respondent then elaborated that their modest logistics solutions for incoming goods worked because they were small. Still, they were also aware that if they want to grow, a solution that facilitates scaling is needed, and that is enabling growth. The company continued to address immediate needs and implement scalable solutions that supported its continued growth. Ultimately, Viola emphasised that enabling growth involves more than reacting to current challenges. Proactive planning and investing in scalable solutions are required to position themselves for sustained growth.

During the interview, Viola also underscored the importance of Change Management skills in navigating dynamic environments such as Wolt's rapid scaling. As people tend to resist change, meaningful management is essential for customers and couriers to navigate transitions.

9.2 Technological aspect point of view

Usama Ali has earned an extensive background in the data-driven field through his academic background in Industrial Engineering, previous role in Customer Support Analytics (Stora Enso) and current position as a Data Integration Engineer (Stora Enso). The interviewee's constant pursuit of knowledge, including self-education in SQL and Power BI courses offered online, enhances the interviewee's credibility in imparting knowledge for ML applications.

Systems Integration. Usama started by providing a general ML workflow comprising Training> Comparing different models> Deployment> Maintenance. The respondent added that the first two stages involve continuous data transformation, highlighting that accuracy is observed in each step. On the other hand, for larger-scale investments, systems would include the cloud, pipelines and production operations. As per data requirements, Usama enumerated data sources in his marine transportation work: ship movements and engine information gathered through their Application Programming Interface (API, which allows applications to interact), several applications and even manual data. While there are several where information can be extracted from, Usama explains that data comes in multiple formats; thus, transforming it to get accepted by their database is a requirement.

Time. Based on his experience and data knowledge, Usama provided a concrete answer regarding the time frame and the question of how long an ML project requires to see tangible results based on experience. In response, the interviewee estimated that three months is a substantial time to realise an actual result, such as model production. On the other hand, this could take longer-- even years—for more advanced projects.

In reaction to the question about ensuring data quality as time is crucial in curating relevant solutions, the respondent replied that in his role as a data engineer, he frequently uses test environments. Usama acknowledges that there can be quality problems with data; therefore, every step it goes through must be examined and verified. When further asked about the accepted accuracy percentage, Usama answered that 80% is acceptable but lower than is not. Finally, time management and developing strategy are crucial to delivering timely and accurate insights, Usama added.

Cost. Drawing from experience with large companies and ample resources, the interviewee emphasises that investing in digital projects is not a question at all. However, Usama recommends carefully considering the value vs. the cost, especially for smaller companies treading cautiously. Furthermore, the interviewee highlights that the financial implications of such ventures can vary depending on the size of a company. Moreover, the cost of ML investment is nothing compared to the output of the solutions.

Further insights: The respondent was questioned about important lessons learned throughout the development and implementation of ML in the culmination of the interview. Usama responded that while technological endeavours may not be as successful as anticipated, which is a typical part of the process, the interviewee mentioned that there will always be learnings from every experience. Adding Research and Development (R&D) can also have a huge impact. Lastly, Usama stated when adopting ML solutions, "Don't be afraid, the results might surprise you".

9.3 Key takeaways and results

Based on the first conducted interview, integration of systems at Wolt together with ML algorithms plays a crucial role in streamlining data collection, optimising their operations, and eventually serving their employees, couriers and customers. The company utilises its app to gather data from various sources, including customers, employees, stores, and couriers, allowing them to get valuable insights and take actions backed up by reliable information. Viola pointed out the complexity of manually navigating these processes, highlighting the necessity for automated solutions. In addition, ML algorithms help anticipate courier arrival times and adjust operations accordingly, enhancing efficiency and service consistency. Moreover, the data acquired through different interactions also provides real-time updates for customers and the application of this information for operational improvements.

Regarding cost considerations, while numbers are undisclosed, Viola stressed to justify judgment by taking measures such as cost-benefit analysis. Moreover, Wolt's strategy on universal systems across different country operations maximises cost-efficiency. Analysing these considerations, it is evident that Wolt tactically integrates systems, time management and cost-efficiency to maintain industry competitiveness. An organisation using a data-driven decision approach and a proactive attitude towards technological development reflects on their core as a tech company.

Regarding time considerations, Wolt prioritises setting goals and frequent road mapping to ensure immediate progress, especially as they continue to expand into new markets. While Viola notes the challenges of new systems as the company grows, early adoption could mitigate these difficulties.

Usama highlights from a technological standpoint, outlining successful system integration, time management, and cost considerations that affect the implementation of ML projects. In terms of systems integration, Usama highlighted the different workflows and systems depending on the scale of a project. As data generally comes in various formats, the need for this initial requirement is of utmost importance. Regarding cost, Usama acknowledges the significance of putting finances into digital initiatives, especially for large companies with extensive resources.

.

Beyond the cost, time, and systems integration factors, respondents shared what they learned from adopting ML within their operations. Wolt's driven leaders and rapid growth case imply the value of recognising the need for scalable solutions to accommodate growth while addressing current needs. In addition, sustaining growth would require proactive planning and meaningful management to get all the stakeholders on board the transition. On the other hand, Usama acknowledges the importance of recognising the worth of experiences in developing ML solutions. Leveraging past experiences, both successful and unsuccessful, to contribute to advancing ML adoption.

10 Results and Discussion

The limitation of this thesis stems from the author's lack of experience and education in machine learning. However, efforts have been made to minimise this limitation through interviews with business and technological experts to ensure a comprehensive exploration of the topic and enhance the quality of the paper. Additionally, it is essential to note that other equally important aspects crucial for ML adoption, such as ethics, law, and security (Paleyes et al., 2022), have not been discussed within the scope of this study.

The central theme of this paper is to provide valuable insights for companies seeking to apply ML solutions in their operations. AI has gained popularity, and ML as its subset may cause confusion between these two fields. Thus, the first section discusses the nature and concept of ML as a multidisciplinary field that enables computers to uncover significant insights and patterns from data (Kashyap 2018). The idea of machines analysing and automising work to a certain degree is not new, just as ML. The pursuit of large companies such as IBM's Deep Blue, developing the field through board games, rooted in their structured yet complex nature, has been pivotal to showcasing its ability to analyse 200 million positions per second (Lu & Li 2022) and (Achenbach 1997). Ushered by computational capacity, ML underwent a significant transformation, shifting from a knowledge-driven approach to one fueled by data abundance (Marr 2016).

Section 3 examined the ML types, depending on the kind of data and whether the training sets were labelled. Supervised learning uses labelled data sets, commonly applied in image recognition and recommendation systems (Serrano 2019). Unsupervised techniques can be processed without labelled data, an effective means of identifying links that may be hidden in massive datasets and could identify new connections that have not been established. Applying reward-punishment in reinforcement learning provides a training ground for situations where everything is unknown, providing insights into navigating complex situations. While one of the strengths of ML lies in its ability to process complex data more quickly, its attributes also encompass weaknesses related to complexity and nuances. Moreover, Cady (2021:2) stressed the importance of incorporating human judgement in making algorithmic rules, measuring their effectiveness and constant monitoring. Keeping these things in mind, the success of machine learning applications does not always depend on complex functions or models; incorporating business insights is just as crucial to the technology's applicability in real-world scenarios.

Today, Wiseri et al. (2022) underscore ML as a pivotal catalyst in the digital revolution, offering unparalleled efficacy and enhancing operational efficiency in logistics. Supported by statistical principles and computer science, ML's ability to navigate intricate and large datasets provides immediate insights for individuals to act on immediately. ML in logistics has become visible across significant activities such as transportation, inventory and warehousing, making it a diverse and multifaceted tool. ML optimises various activities, ultimately reducing costs and increasing customer satisfaction. However, the unique applications of ML in transportation, inventory, and warehousing demonstrate that solutions are based on specific considerations, resulting in tailored solutions. Therefore, applying ML to diverse scenarios, even within similar logistics activities, requires additional work and refinement.

By exploring the foundational concepts of ML, including its development, types, and current applications, organisations can develop an understanding of how ML can be used as a tool to drive innovation and efficiency. However, the successful implementation of ML requires careful consideration of several key factors, as discussed in this paper.

Since data is vital to any ML application, integration with existing systems is the backbone of ML workflow. The emergence of cloud platforms provides end-to-end solutions for web-based environments, ensuring a seamless flow of data across different processes. However, the feasibility of integrating ML solutions with existing systems varies depending on the size and resources, which could deter smaller companies. Remarkably, ML solutions are not limited to sophisticated systems; smaller enterprises can also focus on simpler approaches, more straightforward based on their need, available for free from major tech companies, consulting firms or various third-party solution providers. Moreover, challenges persist in deployment and integration from training to deployment. Thus, a systematic approach and continuous evaluation are necessary.

For enterprises, AI and ML adoption tends to be slower and more costly than anticipated (Algorithmia 2020:15). Also, a survey result on ML State indicated a low percentage of companies successfully building complex systems. This could be due to the time-building models and frequent evaluation in each stage to ensure data quality. In addition, the reality of adopting and changing systems is a lengthy process. However, there are indications of a rise in the commercialisation of AI and ML technologies, speeding up adoption and allowing more enterprises to derive value from their technological ventures.

The financial aspects of ML adaptation are complex and variable. Costs depend on factors such as company size, technological requirements, and deployment strategies, where estimates are laid out in Section 6.3. Thus, no definite information on prices is readily available. Moreover, the section on financial considerations underscores the importance of understanding costs and investment strategies for organisations aiming to leverage ML applications. For smaller companies looking to adopt ML, starting with basic products enables adaptable changes and viability assessments. In general, the section highlights the significance of conducting comprehensive research on the entirety of the investment to overcome barriers and avoid further costs.

Most of the papers reviewed highlighted organisational aspects and the critical considerations of cost, time, and systems integration. This underscores the role of management in encouraging innovation and navigating barriers when stakeholders collaborate closely. Kruhse-Lehtonen and Hofmann (2020) noted that a shared plan and close collaboration between data and business functions ensure measurable and lasting results.

11 Conclusion

The discussion on the ML process shows how ML’s ability to process huge amounts of data and extract connections from it makes it a powerful tool in today’s data-driven logistics. With different facets of ML application, its usage can be applied to various problems. The research topic of whether a business should use ML applications is addressed by this. Businesses that have access to abundant data and intend to use technology supported by facts to enhance operations and customer experience stand to gain the most from this. With different facets of ML application, its usage can be applied to various problems. However, the adoption of machine learning also presents multifaceted challenges, where considerations of cost, time, and systems integration play pivotal roles. Hence, a successful adoption requires a strategic approach to balance these factors.

Furthermore, most of the literature and sources examined for this paper lack a precise blueprint regarding cost, time and systems integration aspects. Instead, the discussion turned into ML intricacies. This may be explained by research findings that indicate a small number of businesses utilising ML in its entirety. In addition, the lack of information could be attributed to this study's limited scope, as other equally significant aspects, such as security and ethics, are pivotal to implementing ML. The lack of widespread use of machine learning (ML) in business makes it more important than ever for organisations to assess what kind of machine learning solutions they need. This is because the size of the project will dictate the infrastructure, time, and cost requirements.

Moreover, the insights gathered from the interviews conducted for this research have provided valuable contributions to understanding the challenges and opportunities associated with adopting ML solutions. The firsthand experiences shared by industry experts have addressed vital considerations such as time, cost, and system integration, offering practical insights for organisations considering embarking on their ML journey. Furthermore, the emphasis on proactive planning and willingness to adapt to technological shifts underscores the importance of a strategic and adaptive approach. By adding these findings, this research has offered actionable recommendations to guide enterprises in overcoming the challenges of ML adoption and achieving success in their innovative efforts. Lastly, ML adoption presents both opportunities and challenges for companies in the logistics industry. By implementing these recommendations, organisations can position themselves in the ML market, navigating complexities of time, cost and systems integration.

References

Achenbach, J., 1997. In Chess Battle, Only the Human Has His Wits About Him. *The Washington Post*, 10 May 1997.

Adekunle, S.A., & Ruth, I., 2023. Technological adoption in logistics management: Review of literature and agenda setting. *Lagos Journal of Geographic Issue*, 3(1), 119-134).

Akbari, M., and Do, T.N.A., 2020. A systematic review of machine learning in logistics and supply chain management: current trends and future directions. [online] Available at:< http://tinyurl.com/3vcnjh2u> [Accessed 06 February 2024].

Algorithmia, 2020. *2020 state of enterprise machine learning*.

Alpaydin, E., 2016. Preface. *Machine learning: the new AI*. London: The MIT Press.

AJOT, 2020. Transport and logistics: delivering global road safety [online] Available at:< https://www.ajot.com/news/transport-and-logistics-delivering-global-road-safety> [Accessed 11 February 2024].

Amann, A., 2021. *Machine learning algorithm or machine learning model?* [online] Available at:< https://www.techopedia.com/machine-learning-algorithm-or-machine-learning-model/7/34855#> />[Accessed 08 October 2023].

Ashmore, R., Calinescu, R. and Paterson, C., 2021. Assuring the machine learning lifecycle: Desiderata, methods, and challenges. *ACM Computing Surveys (CSUR),* 54(5), pp.1-39.

AWS, n. d. *Amazon Machine Learning Solutions Lab?* [online] Available at:< https://aws.amazon.com/ml-solutions-lab/#>[Accessed 08 April 2024].

AWS Documentation, n. d. *ML lifecycle phase- Deployment* [online] Available at:< https://docs.aws.amazon.com/wellarchitected/latest/machine-learning-lens/ml-lifecycle-phase-deployment.html> [Accessed 15 April 2024].

Bonaccorso, G., 2018. *Machine Learning Algorithms*. 2nd edn. Birmingham: Packt Publishing Ltd.

Brown, S., 2021. *Machine learning, explained*. MIT SLOAN SCHOOL OF MANAGEMENT. [online] Available at:<https://mitsloan.mit.edu/ideas-made-to-matter/machine-learning-explained> [Accessed 11 October 2023].

Carleo, G., Cirac, I., Cranmer, K., Daudet, L., Schuld, M., Tishby, N., Vogt-Maranto, L. and Zdeborová, L., 2019. Machine learning and the physical sciences, *APS,* [online] Available at:< https://link.aps.org/accepted/10.1103/RevModPhys.91.045002> [10 October 2023].

Cady, F., 2021. Data Science: *The Executive Summary: A Technical Book for Non-Technical Professionals*. 1st edn. Hoboken: John Wiley & Sons Inc.

Cichosz, M., Wallenburg, C.M. and Knemeyer, A.M., 2020. Digital transformation at logistics service providers: barriers, success factors and leading practices. The International Journal of Logistics Management, 31(2), pp.209-238.

Chui, M., Manyika, J. and Miremadi, M., 2016. *Where machines could replace humans-and where they can't (yet).* [online] Available at:< http://dln.jaipuria.ac.in:8080/jspui/bitstream/123456789/2951/1/Where-machines-could-replace-humans-and-where-they-cant-yet.pdf> [Accessed 03 November 2023].

Coghill, G., 2023. Artificial Intelligence (and Christianity): Who? What? Where? When? Why? and How? *Studies in Christian Ethics*, 36(3), 604-619.

Cong, Z., Luo, X., Pei, J., Zhu, F. and Zhang, Y., 2022. Data pricing in machine learning pipelines. Knowledge and Information Systems, 64(6), pp.1417-1455.

Coop, R., 2020. *What is the Cost to Deploy and Maintain a Machine Learning Model?* [online] Available at:< https://www.phdata.io/blog/what-is-the-cost-to-deploy-and-maintain-a-machine-learning-model/> [Accessed 03 April 2024].

Cordeschi, R., 2007. AI TURNS FIFTY: REVISITING ITS ORIGINS. *Applied Artificial Intelligence*, 21(4-5), pp.259–279.

Dike, H.U., Zhou, Y., Deveerasetty, K.K., and Wu., Q., 2018. 'Unsupervised Learning Based On Artificial Neural Network: A Review', *2018 IEEE International Conference on Cyborg and Bionic Systems*. Shenzhen, China, IEEE, pp. 322-327.

Epstein, R., Roberts, G., & Beber, G., eds. 2008. *Parsing the Turing Test : Philosophical and Methodological Issues in the Quest for the Thinking Computer*. Dordrecht : Springer Netherlands.

De Muynck, B., 2023. The True Role Of AI In Logistics, *Forbes* [online]. Available at:< https://emerj.com/ai-sector-overviews/artificial-intelligence-at-dhl-two-applications/ >[Accessed 17 March 2024].

DeNittis, N., 2023. Artificial Intelligence at DHL- Two Applications at the Wolrd's Largest Logistics Company, *EMERJ Artificial Intelligence Research* [online]. Available at:< https://emerj.com/ai-sector-overviews/artificial-intelligence-at-dhl-two-applications/ >[Accessed 17 February 2024].

Fradkov, A., 2020. Early history of machine learning. *IFAC*, 53(2), pp.1385-1390.

GeekforGeeks, 2023. *How Amazon Uses Machine Learning.* [online] Available at:< https://www.geeksforgeeks.org/how-amazon-uses-machine-learning/> [Accessed 06 January 2024].

Gendler, A., 2016. *The Turing test: Can a computer pass for a human?,* TedEd. [video] Available at:< https://www.youtube.com/watch?v=3wLqsRLvV-c> [Accessed 27 October 2023].

Gocmen, E. and Erol, R., 2019. Transportation problems for intermodal ¨ networks: Mathematical models, exact and heuristic algorithms, and machine learning. *Expert Systems with Applications*, 135, pp.374-387.

Google Cloud, 2023. AI vs. Machine Learning: How Do They Differ? [online] Available at: <https://cloud.google.com/learn/artificial- intelligence-vs-machine-learning> [Accessed 5 October 2023].

Haidine, A., Salmam, F.Z., Aqqal, A. and Dahbi, A., 2021. *Artificial Intelligence and Machine Learning in 5G and beyond: A Survey and Perspectives. In Moving Broadband Mobile Communications Forward-Intelligent Technologies for 5G and Beyond*. London: INTECHOPEN LIMITED.

IBM, nd. What is supervised learning? [online] Available at:<https://www.ibm.com /topics/supervised-learning>[Accessed 17 October 2023].

Jackson, A., 2024. Top 10: Machine Learning Companies *, AIMAGAZINE* [online] Available at:< https://aimagazine.com/top10/top-10-machine-learning-companies> [Accessed 28 March 2024].

Jeske, .M., Grüner, M., and Weiß, F., 2020. *BIG DATA IN LOGISTICS*. [online] Available at:< https://www.dhl.com/content/dam/dhl/global/core/documents/pdf/glo -core-big-data-trend-report.pdf> [Accessed 05 February 2024].
Jones, S., & Groom, F., eds. 2019, Artificial Intelligence and Machine Learning for Business for Non-Engineers. Boca Raton: Taylor & Francis Group.

Kashyap, P., 2018. *Machine Learning for Decision Makers.* [e-book] Bangalore: Apress. Available through: Metropolia University of Applied Sciences Library, <http://www. metropolia.fi/en/services/library/> [Accessed 10 October 2023].

Keary, T., 2024. *Top 10 Countries Leading AI Research & Technology in 2024.* [online] Available at:< https://www.techopedia.com/top-10-countries-leading-in-ai-research-technology>[Accessed 27 March 2024].

Krishnan, R., Perumal, E., Govindaraj, M., & Kandasamy, L., 2024. Enhancing Logistics Operations Through Technological Advancements for Superior Service Efficiency. *IGI Global,* 4:61-82.

Kruhse-Lehtonen, U., and Hofmann, D., 2020. How to Define and Execute Your Data and AI Strategy, *Harvard Data Science Review*. [online] Available at: < https: //hdsr.mitpress.mit.edu/pub/4vlrf0x2/release/2>[Accessed 10 April 2023].

Kuntz, D. and Wilson, A., 2022. Machine learning, artificial intelligence, and chemistry: How smart algorithms are reshaping simulation and the laboratory. *Pure and Applied Chemistry*, 94 (8), pp. 1019-1054.

Kongsbak, A.S., and Morville, T., n.d. Machine learning in Transport & Logistics, *Monstarlab*.[online] Available at:< https://monstar-lab.com/builder/assets/ pdf/Machine-learning-whitepaper-New.pdf> [Accessed 27 March 2024].

Lee, I. and Shin, Y.J., 2020. Machine learning for enterprises: Applications, algorithm selection, and challenges. *Business Horizons*, 63(2), pp.157-170.

Lum, K. and Chowdhury, R., 2021. What is an" algorithm"? It depends whom you ask, *MIT Technology Review* [online] Available at:<https://www.technologyreview.com /2021/02/26/1020007/what-is-an-algorithm/> [Accessed 11 November 2023].

Marr, B., 2016. A Short History of Machine Learning—Evey Manager Should Read, *Forbes* [online] Available at:< https://www.forbes.com/sites/bernardmarr/ 2016/02/19/a-short-history-of-machine-learning-every-manager-should-read/> [Accessed 27 October 2023].

McKinsey, 2022. The data-driven enterprise of 2025. [online] Available at:< https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-data-driven-enterprise-of-2025>[Accessed 27 March 2024].

Microsoft Azure, n.d. Azure for medium and small businesses. [online] Available at:< https://azure.microsoft.com/en-us/solutions/medium-small-business-cloud-computing#pricing >[Accessed 10 April 2024].

Mirashe, S. and Kalyankar, N.V., 2010. Cloud Computing. *Journal of Computing*, 2 (3), pp. 2-3.

Mitchell, T., 1997. Machine learning (Vol. 1, No. 9). New York: McGraw-hill.

Mohammed, M., Khan, M.B., & Bashier, E., 2017. *Machine learning : algorithms and applications*. [e-book] Available at:< https://learning.oreilly.com/library/view/machine-learning/9781315354415/xhtml/copy.xhtml> [Accessed 23 November 2023].

Mohri, M., Rostamizadeh, A. and Talwalkar, A., 2018. *Foundations of machine learning.* MIT Press.

Moore, S., 2019. *Gartner Top 10 Data and Analytics Trends for 2019*. [online] Available at:< https://www.gartner.com/smarterwithgartner/gartner-top-10-data-analytics-trends>[Accessed 19 April 2024].

Mueller, J.P., & Massaron, L., 2016, *Machine Learning for Dummies*. Hoboken, New Jersey: John Wiley & Sons, Incorporated.

Norman, J., 2024. McCulloch & Pitts Publish the First Mathematical Model of a Neural Network, History of Information. [online]. Available at:<https://www.history ofinformation.com/detail.php?entryid=782> [Accessed 07 January 2024].

Ozan., Ş., 2018. A Case Study on Customer Segmentation by using Machine Learning Methods, IEEE Xplore. [online] Available at:< https://ieeexplore.ieee.org/abstract /document/8620892> [Accessed 23 November 2023].

Paleyes, A., Urma, R.G. and Lawrence, N., 2022. Challenges in deploying machine learning: a survey of case studies. ACM computing surveys, 55(6), pp.1-29.

Praveen, K.B., Prateek J., Pradyumna, K., Pragathi, J., and Madhuri, J., 2020. Inventory Management using Machine Learning. *International Journal of Engineering Research & Technology,* 9(6), 866-899.

Ragin, C.C., 2004. Introduction to session 1: Defining qualitative research. In Workshop on Scientific Foundations of Qualitative Research (Vol. 22).

Ryzhkov, A., 2023. *How Much Does Machine Learning Cost for Maximized ROI and Financial Services?* [online] Available at:< https://finmodelslab.com/blogs/startup-costs/machine-learning-for-financial-services-startup-costs> [Accessed 23 March 2024].

Saha, D. 2019. How The World Became Data-Driven, And What's Next, *Forbes* [online]. Available at: < https://www.forbes.com/sites/googlecloud/2020/05/20/how-the-world-became-data-driven-and-whats-next/> [Accessed 30 October 2023].

Santo, B., 2019. THE CONSUMER ELECTRONICS HALL OF FAME: AMAZON ECHO DOT, IEEE [online] Available at:< https://spectrum.ieee.org/the-consumer-electronics-hall-of-fame-amazon-echo-dot> [Accessed 27 January 2024].

Saunders, L., 2020. 3. Learning Theories: Understanding How People Learn. [online] Available at:<https://iopn.library.illinois.edu/pressbooks/instructioninlibraries/chapter/learning-theories-understanding-how-people-learn/>[Accessed 05 December 2023].

Serrano, L., 2019. *Grokking Machine Learning.* [livebook] Manning Publications. Available at: <https://livebook.manning.com/book/grokking-machine-learning/copyright-2019-manning-publications/v-4/4>[10 December 2023].

Sharma, D. and Kumar, N., 2017. A review on machine learning algorithms, tasks and applications, *International Journal of Advanced Research in Computer Engineering & Technology,* 6(10), pp-1548-1552.

Shashkina, V., 2024. Calculating machine learning costs: price factors and estimates from the ITRex portfolio [online] Available at:< https://itrexgroup.com/blog/machine-learning-costs-price-factors-and-estimates/> [Accessed 10 April 2024].

Shen, S., 2020. What is Data?, *Towards Data Science* [online] Available at:< https://towardsdata science.com/what-is-data-ade94b37204a> [Accessed 03 November 2023].

Silva, N., Shah, V., Soares, J. and Rodrigues, H., 2018. Road Anomalies Detection System Evaluation. *Sensors*, 18(7), p.1984.

Sing, A., Wiktorsson, M., and Hauge, J.B., 2020. Trends In Machine Learning To Solve Problems In Logisitcs. *CIRP*, 103(1), 67-72.

Soofi, A.A. and Awan, A., 2017. Classification techniques in machine learning: applications and issues. *Journal of Basic & Applied Sciences*, 13(1), pp.459-465.

Srivastava, S., 2023. AI in Logistics Industry:Key Benefits and Use Cases. [online] Available at: <https://appinventiv.com/blog/ai-in-logistics-industry/>[Accessed 25 October 2023].

Statista, 2019. eCommerce Report 2019 | *Statista*. [online] Available at: <https://www .statista.com/study/42335/ecommerce-report/> [Accessed 06 February 2024].

Stone, H., 1971. *Introduction to Computer Organization and Data Structures*. New York: McGraw-Hill, Inc.

Steer, G. and Dempsey, H., 2021. *Introduction to Computer Organization and Data Structures*. New York: McGraw-Hill, Inc.

Symeonidis, G., Nerantzis, E., Kazakis, A. and Papakostas, G.A., 2022, January. MLOps-definitions, tools and challenges. *IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC)*, Las Vegas, USA, (pp. 0453-0460).

The Economist, 2017The world's most valuable resource is no longer oil, but data. [online] Available at:< https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data> [08 March 2024].

Taylor, P., 2023. *Volume of data/information created, captured, copied, and consumed worldwide from 2010 to 2020, with forecasts from 2021 to 2025*, Statista. [online] Available at:<https://www.statista.com/statistics/871513/worldwide-data-created/ [Accessed 10 December 2023].

Theobald, O., 2017. *Machine Learning for Absolute Beginner.* [e-book] Available at:< https://bmansoori.ir/book/Machine%20Learning%20For%20Absolute%20Beginners.pdf>[Accessed 08 January 2024].

Toosi, A., Bottino, A., Saboury, B., Siegel, E. & Rahmim, A., 2021. A brief history of AI: how to prevent another winter (a critical review), *PET Clinics*, 16 (4), pp449-469.

University of York, 2023. *What is data?* [online] (Last Updated 27 November). Available at: <https://subjectguides.york.ac.uk/data/lore>[Accessed 10 December 2023].

University of York, 2023. *What is data?* [online] Available at: <https://subject guides.york.ac.uk/data/lore>[Accessed 10 December 2023].

Wakefield, K., nd. *A guide to machine learning algorithms and their applications*, SAS. [online] Available at:< https://www.sas.com/fi_fi/insights/articles/analytics/machine-learning-algorithms-guide.html> [Accessed 27 November 2023].

White, O., 2023. \`How our interconnected world is changing\`, McKinsey Global Institute [podcast] Available at:<shttps://www.mckinsey.com/mgi/our-research/how-our-interconnected-world-is-changing> [Accessed 18 February 2024].

Wiseri, W., Donthu, S., Mehbodniya, A., Vyas, S., Quiñonez-Choquecota, J. and Neware, R., 2022. An investigation on the impact of digital revolution and machine learning in supply chain management. Materials Today: Proceedings, 56, pp.3207-3210.

Wolt, n.d. IT'S STORY TIME. [online] Available at:< https://careers.wolt.com/en/story > [Accessed 08 April 2024].

Wuest, T., Weimer, D., Irgens, C. and Thoben, K.D., 2016. Machine learning in manufacturing: advantages, challenges, and applications. *Production & Manufacturing Research*, 4(1), pp.23-45.

Yu, X., Liao, X., Li, W., Liu, X. and Tao, Z., 2019. Logistics automation control based on machine learning algorithm. *Cluster Computing*, 22, pp.14003-14011.

Zadgaonkar, H., and Chandak, M., 2021. Locating Objects in Warehouses Using BLE Beacons & Machine Learning. *IEEE*, 9, pp. 153116-15.

Zantalis, F., Koulouras, G., Karabetos, S., & Kandris, D., 2019. A Review of Machine Learning and IoT in Smart Transportation. *Future Internet*, 11(4):94.

Appendices

Questionnaire 1

1. Could you provide an overview of how machine learning is currently used in your operations?
2. What prompted your company to adopt machine learning solutions?
3. What kind of data do you use, and where were they extracted?
4. How did you integrate machine learning technologies with existing systems?
5. While cost can vary depending on factors such as customisation and scalability, could you offer any insights into the financial implications or cost considerations related to implementing machine learning solutions into practice? These would greatly help companies in their decision-making process.
6. What organisational transformations were necessary to integrate machine learning into your operations?
7. How do you handle situations where machine learning results or recommendations conflict with human insight?
8. What were your main goals in adopting machine learning? Were they met? If so, how long did it take to achieve?
9. Can you describe a successful implementation of a machine learning application within your operations, including challenges and lessons learned?
10. What strategies do you employ to ensure continuous improvement of machine learning applications in response to market dynamics and business needs?
11. Can you share any examples of unexpected benefits or opportunities that arose from the adaptation of machine learning in your operations?
12. What advice would you give to companies that are considering machine learning solutions to enhance their operations?

Questionnaire 2

1. Could you provide a background regarding your knowledge or expertise?
2. Could you provide an overview of how machine learning is currently based on your experience? Any typical workflow for implementing ML solutions from gathering data to deployment?
3. What kind of data do you use, and how were they extracted? How important is the iteration process?
4. While cost can vary depending on factors such as customisation and scalability, could you offer any insights into the financial implications or cost considerations related to implementing machine learning solutions into practice? Total Cost of Ownership? (These would greatly help companies in their decision-making process).
5. Could you share the ratio of cost investment with respect to cost savings of an ML solution?
6. How long do ML projects require to see a tangible result based on your experience?
7. As time is essential in curating relevant solutions, how do you ensure quality results? Is there a strategy used to accelerate development and deployment?
8. Can you explain how the ML system is integrated with existing systems or workflows?
9. Can you share an example of ML-driven insights leading to actionable decisions?
10. Are you involved in measuring the effectiveness and efficiency of ML in business solutions? What were some performance indicators?
11. Do you have any insights or experience on the crucial role of organisations in the success of implementing ML solutions?
12. What advice would you give to companies that are considering machine learning solutions to enhance their operations?

List of Figures and Tables