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The impact of Artificial Intelligence in the Rail Industry

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Department of Marketing, Strategy and Operations

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Resumo

A Inteligência Artificial (IA) está a ser implementada em sistemas empresariais devido aos benefícios que esta tecnologia disruptiva pode apresentar, mesmo tendo em conta os riscos e desafios associados. Na indústria ferroviária, a IA está a ser aplicada para melhorar os atrasos na chegada de comboios, para reduzir os custos de manutenção tradicionais de comboios e da infraestrutura, e para melhorar a experiência do cliente. No que diz respeito ao transporte intermodal, esta tecnologia pode melhorar o fluxo de passageiros dentro dos *hubs*, evitar perdas de mercadoria e melhorar a sua monitorização dentro dos terminais logísticos. O objetivo desta investigação é o estudo do impacto da Inteligência Artificial na indústria ferroviária e, para tal, foi usada uma metodologia quantitativa para responder a três questões de pesquisa. Primeiramente, ocorreu uma análise das diferenças de fatores sociodemográficos no conhecimento de IA. Posteriormente, ocorreu também uma análise da influência dos benefícios, riscos e confiança na implementação da tecnologia de IA nos sistemas desta indústria e, adicionalmente, para expandir esta investigação para além da indústria ferroviária, ocorreu uma análise do impacto da IA nos sistemas de transporte intermodais. Os resultados obtidos permitem demostrar que existem diferenças sociodemográficas entre os inquiridos e existe também a confirmação da influência que os benefícios, riscos e confiança podem trazer para a implementação de IA nesta indústria. No que diz respeito aos sistemas de transporte intermodal, os mesmos efeitos já referidos e adicionalmente da noção da IA na implementação destes sistemas, são confirmados.

Palavras-chave: Inteligência Artificial, Indústria Ferroviária, Transporte Intermodal

Classificação JEL:

L92 – Railroads and Other Surface Transportation

O32 – Management of Technological Innovation and R&D

Abstract

Artificial Intelligence (AI) is being introduced in enterprise systems due to the promising benefits that such a disruptive technology can present, even when taking into account its risks and challenges. In the rail industry, AI is being implemented to help improve train delays, reduce infrastructure and rolling stock maintenance costs, and to improve customer's experience. In intermodal terminals, this technology helps improve passenger flow through hubs, avoids freight cargo losses and improves cargo monitoring inside the terminals. The aim of this investigation is to study the impact of Artificial Intelligence in the rail industry, and, in order to conduct this investigation, a quantitative methodology approach was used to answer three research questions. Initially, an analysis of the differences of sociodemographic factors on the knowledge about AI occurred. Posteriorly, an analysis of the influence of the benefits, risks and trust on the implementation of AI in the rail industry was conducted and, in order to expand the scope of the study outside the rail industry, an analysis of the impact of AI in the intermodal transportation systems was completed. The results show that sociodemographic differences among the respondent's knowledge about AI exist, along with the confirmation that the factors of benefits, risks and trust influence the implementation of AI in the rail industry. Regarding intermodal transport systems, the same effects and additionally the awareness of AI were proved to influence the implementation of these kinds of systems.

Keywords: Artificial Intelligence, Rail Industry, Intermodal Transportation

JEL Classification:

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Glossary of Acronyms

AI – Artificial Intelligence

ANOVA - Analysis of variance

AVE – Average Variance Extracted

CR - Composite Reliability

DF – Degrees of Freedom

DL – Deep Learning

HSR – High Speed Rail

HST – High Speed Train

HTMT - Heterotrait-Monotrait Ratio

IoT – Internet of Things

IT – Information Technology

ML – Machine Learning

NLP – Natural Language Processing

NN – Neural Networks

PLS – Partial Least Squares

R&D – Research and Development

RQ – Research Question

SEM – Structural Equation Modelling

STDEV – Standard Deviation

TS – Train Scheduling

VIF - Variance Inflation Factor

WWW – World Wide Web

Introduction

Framework

According to Russell and Norvig (2021), “We call ourselves Homo sapiens because our intelligence is so important to us. For thousands of years, we have tried to understand how we think and act.” (p. 19). With the development of Artificial Intelligence, not only is the human mind more understood than ever but there are subfields of AI with the specific purpose of mimicking the human brain. As new uses for AI are still being discovered, its applications in different industries are also being studied. In Medicine (Mendes, 1997; Ding et al., 2019; Mesquita, 2017) it is being used for diagnosis purposes; in Marketing and Sales, AI algorithms are used in order to improve recommendations to customers based on past experiences (Haenlein & Kaplan, 2019; Martínez Lopez & Casillas, 2013) and in Robotics, it is being used to develop machinery capable of reducing repetitive human labor (Yin et al., 2020).

In the rail industry the application of AI can help maintain a cost leadership strategy while maintaining the quality of service (International Union of Rails [UIC], 2021). In the European case, it can “double the capacity of the European rail system and increase its reliability and service quality by 50%, all while halving life-cycle costs.” (Shift2Rail [S2R], 2021, About). AI algorithms have been applied in train scheduling management, maintenance of the rolling stock, maintenance of infrastructures, ticket sales prediction through the help of Machine Learning algorithms, abandoned luggage detection and other operational uses (UIC, 2021).

Specifically, in the transport industry, intermodal transportation is a topic of concern both in cargo and passenger transportation, as they can present delays, cancellations or, in the case of freight, cargo loss (Gambardella et al., 1998). In order to ensure a good intermodal network design, there is a need for a solution to these problems. According to Balster et al. (2020), Artificial Intelligence and its subfields, such as Machine Learning, can be this solution as these technologies can provide accurate timetables of arrivals and departures or to improve the handling of delays or cancellations.

This investigation aims to study the different implementations of AI technologies and algorithms in systems, including both the positive and negative factors associated. A disruptive technology such as Artificial Intelligence can lead to a deployment in systems without taking into account the risks this technology presents, alongside other factors that might originate from its implementation, and they should be measured in order to evaluate their validity and trueness.

This investigation in specific has the objective of the study of these indicators and factors in the rail industry and, additionally, in the intermodal transportation that can be associated with the railway.

Investigation Problem

The main focus of this thesis is to study the impact of Artificial Intelligence in the rail industry and consequently how can a disruptive technology like Artificial Intelligence be applied in a business environment. Although the development of Artificial Intelligence started in the mid of the 20th century, implementations in the different industries started being developed in the last ten to fifteen years (Haenlein and Kaplan, 2019). AI algorithms can be used in order to improve the processing of large amounts of data, implement faster systems in companies or to handle customer's analytics (Lim et al., 2020; Jaakkola, 2020). In the rail industry, Artificial Intelligence is being used in order to plan timetables, reduce delays and to implement *chatbot's* that can improve customer experience (UIC, 2021) and, additionally, in inter modal transportation, it is being used for delay handling, cargo loss prevention and failure adaptability.

With all the positive and negative implications that the implementation of Artificial Intelligence can bring, questions such as the impact of AI in the rail industry should be considered. In order to answer this question, firstly both Artificial Intelligence and the rail industry and the adjacent topic of transport inter modality will be discussed, alongside some implementations of Artificial Intelligence already in use by the different companies and industries. Moreover, an analysis regarding the impact that these factors can bring to the implementation of AI will be conducted following on a previous data collection process.

Theoretical and Empirical Objectives

When talking about the objectives of this investigation and the thesis, both the empirical and theoretical objectives should be considered. The aim of the investigation, namely the theoretical objectives, is to contribute to the research and scientific knowledge in the Artificial Intelligence field and the rail industry, by trying to reduce the literary gap in the AI and rail industry topics, study the impact that the implementation of Artificial Intelligence in the rail industry can bring and provide further research on how Artificial Intelligence and the rail industry can be connected.

Empirically speaking, there are two main objectives and three research questions in total, corresponding to one RQ for the first objective and two for the second. The first objective of *The possibility to implement AI in the rail industry,* tries to analyze the sociodemographic differences related to the knowledge about the technology and to study how can the benefits, risks and trust influence the impact of the implementation of AI in the industry. Similar to the first objective, the second objective, that investigates *The possibility to implement AI in intermodal transportation* tries to assess the impact of the benefits, risks, trust and additionally of the awareness of AI in intermodal transportation systems.

Thesis Structure

In order to investigate the impact of Artificial Intelligence in the rail industry, and its additional focus on intermodal transportation, this thesis is divided into an introduction, five main chapters and a conclusion. This introduction of the thesis presents the investigation and presents the framework about the topic to the reader. Following the introduction, the first two main chapters is where the literature review is explored. The first chapter is on the topic of Artificial Intelligence, where both theoretical and real case scenarios of AI are presented, and the second chapter starts by gives a brief explanation of the railway and then the different applications of AI in the rail industry are presented. Additionally, the topic of inter modality, with a focus on the rail transport is explained and the uses of AI for these kinds of systems are also presented.

The third chapter is where the theoretical approach is explained, by relating the two objectives to their research questions and giving an explanation about each of them. The fourth chapter includes the methodology and the explanation of the tools used in order to collect and analyze the data. Following the methodology chapter, the fifth chapter is the results presentation and discussion, where a statistical analysis of the data from the questionnaires is done using SEM-PLS and the validation of the hypothesis occurs. It is subdivided into three subchapters, each one of those relating to one of the research questions. Finally, the conclusion focuses on the results of the investigation, where suggestions for other future studies are presented and the limitations are discussed, alongside the possible contributions for the industries.

Chapter 1 - Artificial Intelligence

1.1 - Artificial Intelligence concept and definition

Artificial Intelligence (AI) can be seen as the mimicking of human intelligence through the use of machines (Tripathi & Sachin, 2020). According to Russell and Norvig (2021), AI can be defined as the actions that intelligent agents do based on their perception of the surrounding environment. It can also be defined as the methods, tools, and systems that solve problems that usually could only be solved by humans (Costa, 2020). Moreover, AI can also be thought as the ability to solve problems by observing complex systems that exist in the living nature (Costa et al., 2020). Artificial Intelligence is a field that is now present in the business environment and mainstream conversation, a stark contrast from its origins in the 1950s, where it started as a subfield of computer science that had limited practical applications, suffered from hardware limitations and was a topic of restricted interest in the research world (Haenlein & Kaplan, 2019; Ruiz-Real et al., 2020). Consequently, the concept of Artificial Intelligence has evolved, and different authors have proposed different definitions.

Russell and Norvig (2021) classified AI as the combination of four different dimensions: human vs rational and thought vs behavior. The authors relate the human and thought dimension to the *Turing test* (or imitation game). This test had the objective to determine whether a computer could be capable of thinking like a human and is described in the next subchapter. Another approach to the human dimension mentioned by the authors used cognitive modeling, meaning that, in order for a program to be human-like, it must first have to had information of how humans think. On the rational and behavioral dimension, two approaches were described, the first being based on the laws of thought, or formal logic, and the second through the use of rational agents, which can be thought as intelligent machines.

Choi and Ozkan (2019) used a different method in order to define AI. The authors relate the concept to its disruptive technological nature. This disruption, that is intrinsic to itself, is characterized as the way that companies are changing every basic function of their operating model, through the combination of both Artificial Intelligence and Robotics. Some of these basic functions can include the analysis of user behavior and user profiles creation, relating to departments such as marketing and logistics. As seen above, Choi and Ozkan (2019), Costa et al. (2020), Tripathi and Sachin (2020) and Russell and Norvig (2021) all have different definitions of AI, but since the 1950s, the definition of AI has evolved (Table 1.1) over time.

Table 1.1 - AI definitions over the decades (Turing, 1950; Meinhart, 1966; Barr & Feigenbaum, 1981; Cristina et al., 2008)

Definition	Reference
A direct definition was not given, instead a method of inquiry was presented, the Imitation Game.	Turing (1950)
"[…] development of programs that enable a computer to perform mental activities in such a fashion that, if a human performed similarly, it would be called intelligent behavior. The goal of such a program is intelligent behavior, whether a human would act this way or not."	Meinhart (1966)
"It is the part of computer science concerned with designing intelligent computer systems, that is, systems that exhibit the characteristics we associate with intelligence in human behavior."	Barr and Feigenbaum (1981)
"Artificial intelligence is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but artificial intelligence does not have to confine itself to methods that are biologically observable. "	Cristina et al. (2008)

As it can be seen in Table 1.1, the definition of AI has evolved from not being explicitly defined (Turing, 1950) to being related to intelligent behavior (Meinhart, 1966) to finally being defined as a unique field of study that is responsible for the designing of intelligent computer systems (Barr & Feigenbaum, 1981; Cristina et al., 2008). Although, and according to Barr and Feigenbaum (1981), AI started as being a subfield of Computer Engineering, it can be traced back to other areas (Russell & Norvig, 2021).

One of the areas that influenced AI was Philosophy, through the use of formal logic rules applied, for example, in Fuzzy Logic (Mostafa et al., 2018; Yang et al., 2020; Jafarian-Moghaddam, 2021) and additionally with the origin of knowledge concept through various philosophical theories, including dualism, materialism, and empiricism (du Toit, 2019). In

Mathematics, the theory of probabilities and its relation to logic, the use of statistics, and the creation of algorithms led to the development of multiagent systems and game theory (Harré, 2021; Russell & Norvig, 2021). In Economics, the development of the decision theory gave way to the development of the game theory that later constituted one of the bases of multiagent systems. Moreover, operations research also helped to formalize the Markov decision processes and reinforcement learning (Domingos, 2019).

Other areas include Neuroscience, that with the study of the nervous system and the development of the concept of neuron and brain-machine interfaces gave way to, for example, Neural Networks (Urbas, 2020). Psychology is a field that deals with the study of how humans think and act and it is related to the creation of Natural Language Processing and other subfields of AI. The behaviorism movement and cognitive psychology helped to understand the operation of cognitive function. Human-computer interaction helped create the idea of intelligence augmentation, a concept applied similarly in AI algorithms (du Toit, 2019).

According to Russell and Norvig (2021), the main contributor to the development of Artificial Intelligence is Computer Engineering, as the origin of Artificial Intelligence can be traced back as it being a subfield of this field. Since the creation of the modern digital computer and the first programmable computer, each generation of computer hardware has seen an increase in speed. This increase helped ML and AI models getting more efficient and reducing the time needed in order to process data (Lazaridis, 2019; Eddison 2021).

Control theory and cybernetics contributed with the development of control theory and its relation to cognition science, that, together with homeostatic devices, led to cost maximizing function also present in AI (Russell & Norvig, 2021). Finally, Linguistics, which is the study of the relationship between language and thought, evolved roughly at the same time as the creation of computational linguistics or Natural Language Processing (NLP). Furthermore, knowledge representation is also tied to research in linguistics (Castillo, 2021). According to Haenlein and Kaplan (2019), with all of these contributions from the different fields, the development of AI prospered and, since the 1950s up to the present, it continues to grow and allow real-life applications of AI to be implemented.

1.2 - Evolution of Artificial Intelligence

Since the creation of Artificial Intelligence in the 1950s, AI development can be split into different milestones, related to the different eras of AI and the new concepts that appeared. According to Haenlein and Kaplan (2019) and Dewey (2019), the history of AI can be split into four stages, where the inception of AI can be defined as being in the 1940s with the development of the Turing test and the coining of *Artificial Intelligence*. Following this preliminary stage, the prosperity era followed, until the 1960s, where progress was happening swiftly. Research and development of AI slowed in the 1960s and 1970s, due to the lack of government funding and hardware evolution. Since then, AI development has been growing and, in the twenty first century, with the help of the development of the WWW, practical applications started to appear and due to this, Haenlein and Kaplan (2019) believe that an extra stage of exponential growth will exist in the future.

Russell and Norvig (2021) believed that AI's history could be split into four different milestones, each representing a major AI development. The first stage involved Marvin Minsky (1969) and John McCarthy (1971), for developing the basic structure of an IA model in representation and reasoning. The second involved Ed Feigenbaum and Raj Reddy (1994), which developed systems with knowledge systems to solve real-world problems. Judea Pearl (2011) was responsible for developing AI probabilistic techniques and this development was considered as the beginning of the third stage of AI. According to the authors, the last milestone can be attributed to Yoshua Bengio, Geoffrey Hinton, and Yann LeCun (2019) for the creation of multilayer neural networks, also referred to as Deep Learning (DL).

Although Haenlein and Kaplan (2019) and Russell and Norvig (2021) divided the development of AI in different ways, both authors believed that the inception of AI was in the 1940's. According to Haenlein and Kaplan (2019), it was attributed to Isaac Asimov, a science fiction writer, with the short story Runaround, and to Alan Turing, that developed the code-breaking machine *The Bombe* for the British government. The Turing test, originally called the imitation game, was proposed by Alan Turing in 1950, and starts with the author proposing the question 'Can machines think?'. This test (represented in Figure 1.1) starts by an interrogator having a conversation via typed messages with either a program or person for five minutes and, afterwards, the interrogator would have to conclude based on the answers given if the conversation happened with either the computer or the person (Turing, 1950).

The objective of this test is to figure if a machine exhibits intelligent behavior capable of being indistinguishable from a human. According to Schoenick et al. (2017) and Russell and Norvig (2021), in order for a computer to pass this test, it would need natural language processing, in order to mimic the communication of a human being, knowledge representation, as the machine needs to store information based on examples, automated reasoning, in order to answer questions and go to conclusions and ML because the machine needs flexibility in order to recognize patterns and to adapt.

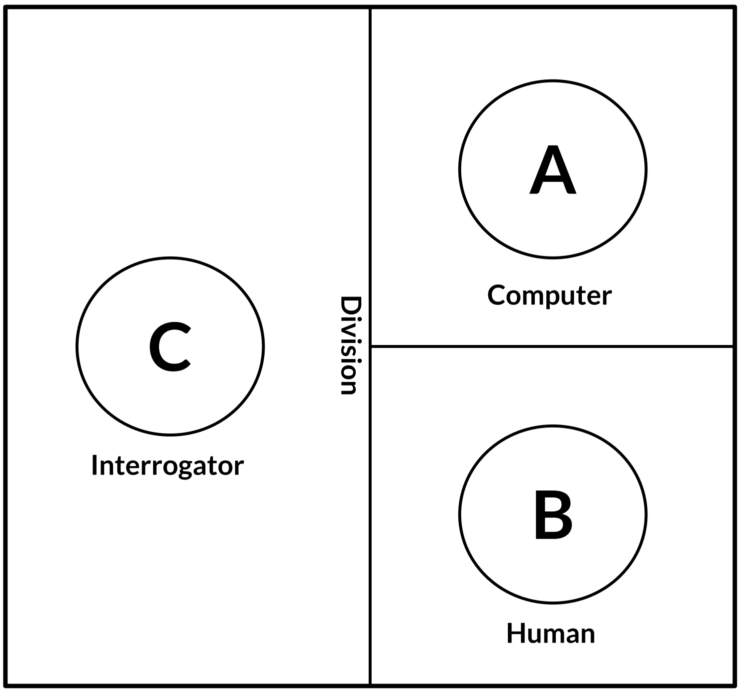

Figure 1.1 – Turing Test (Adapted from Russell and Norvig, 2021)

Russell and Norvig (2021) mention a total Turing test, which not only recognized humans, but additionally, the machine would have the capability to recognize objects and interact with people in the real world. Two extra abilities are then needed, computer vision, due to the fact that the machine needs to understand the real world and robotics, in order to manipulate objects. Although the Turing's test does not refer to AI directly, it was a predecessor to its development and of its multiple subfields.

According to Russell and Norvig (2021), the first developments related to AI were done by McCulloch and Pitts (1943), with a proposal of a network made with artificial neurons. From 1943 until 1956, another neural network was developed, named *Snarc*. The term Artificial Intelligence was coined in 1956 by Marvin Minsky and John McCarthy in a conference hosted by the two authors (Haenlein & Kaplan, 2019).

From 1952 until 1969, a time of great prosperity arose, where the focus was on the replication of tasks in areas that typically required human intelligence, such as medicine and mathematics, with computer machines. During this period, the physical symbol system was created with the objective of manipulating symbol-like data structures. According to Chen (2016), the most important advancement in this period happened because of Arthur Samuel, where he created the basis for reinforcement learning, that later led to the creation of systems such as AlphaGo (Silver et al., 2016).

Other important landmarks were the creation of Lisp in 1958 by John McCarthy, an algorithm that solved first-order logic, and microworlds, such as blocks worlds. From 1966 to 1973, a slowing in AI development happened due to a misunderstanding of how scalability would work, due to the thought that larger problems would be solved with the progress of hardware speed and memory size. Nevertheless, additional reasons such as the failure of governments to support research and a failure to demonstrate how basic structures worked resulted in the delay of, for example, multilayer networks research. (Haenlein & Kaplan, 2019; Russell & Norvig, 2021).

New systems that worked in different ways in order to solve complex problems appeared in the late sixties with the help of an AI system named *Dendral* (Buchanan et al., 1969), a pioneer in the use of domain-specific knowledge. These new methodologies were also called expert systems, due to the fact that it was the first knowledge intensive systems. Another concept that evolved in parallel with expert systems was the certainty factors, used in the medical field in order to address the impact of uncertainty in the diagnosis process. Domain knowledge was tied to language understanding and processing and the growth of applications in the real world led to the creation of new programming languages such as Prolog (Rahimova et al., 2020).

Neural networks (NN) made a comeback in the 1980’s due to the development of the back-propagation learning algorithm and the connectionist model that, in contrast to symbolic and logical models, were more suitable for the real world, due to the lack of rigidity in comparison with the other models, and that, additionally, they could predict values based on past examples. Machine learning (ML) first started being developed in conjunction with probabilistic reasoning. Rigid expert systems that were based on hand coding and Boolean logic were also replaced by more flexible systems that incorporated ML algorithms (Cho et al., 2020; Russell & Norvig, 2021; Eddison 2021).

Big Data started to be developed in the beginning of the twenty-first century due a necessity to process larger amounts of data, as the World Wide Web was rapidly growing starting at the end of the 20th century (Haenlein & Kaplan, 2019). Deep learning’s origins can be traced to as far back as the 1970’s, but it was only in the beginning of the 2010’s that new improved algorithms started being developed (Lazaridis, 2019; Eddison, 2021). The growth of Deep Learning wasn’t exclusive to DL as according to Russell and Norvig (2021), Artificial Intelligence has seen an increase in the number of academic publications published; the number of students that enroll in areas related to AI has been growing, and AI became the most popular specialization in Computer Science. Moreover, the number of conferences, companies created that use AI and real-world applications of AI in companies also increased.

1.3 - Subfields of Artificial Intelligence

Although AI started as a subfield of Computer Engineering, later developments led to the separation into its own separate field of study. Concepts such as ML, DL and NN started being developed in the 1960s, and other subfields related to AI started being developed. According to Mesquita (2017), Machine Learning is a technology that improves its performance based on experience and examples and works by observing the real world and its environment. Russell and Norvig (2021) consider ML as a subfield of AI and, according to the authors, Machine Learning is when an agent (in this case, a computer agent) improves its performance by observing the real world. In ML, in order to solve a problem, a computer will observe and collect data and will build a model based on hypothesis.

ML learning algorithms can be classified into four different types (Russell & Norvig, 2021; Maheshwari, 2021), the first being supervised algorithms, that learn from past examples, and can include the Bayes, nearest neighbor, support vector and linear regression algorithms; semi-supervised algorithms, similar to supervised learning, but these type of algorithm can additionally process unlabeled data; unsupervised algorithms that try to learn patterns from large data sets and finally reinforcement algorithms, that learn from trial and error, such as Neural Networks.

Deep Learning (DL) is a subfield of Machine Learning that uses multiple processing layers in order to train computers to do human-like tasks, such as speech processing. This subfield of AI constructs the output based on both input parameters and past data (Russell & Norvig, 2021). According to Eddison (2021), DL is used to represent data with multiple levels of abstraction using multiple processing layers. The author mentions that one advantage of using Deep Learning is that, when dealing with big data sets, it uses the back propagation method algorithm in order to change the inputs and outputs between layers. These data sets can include, for example, text, images, video, and speech.

Contrary to Machine Learning, that is more rigid in the way that can process raw data into, for example, a simple 2D vector, DL uses multiple layers, that are more abstract the higher the layer that the data is being processed. According to the authors, the most common form of Deep Learning is supervised learning algorithms (similar to those used in ML), that adjusts its inputs and outputs based on data collected (Eddison, 2021). When comparing AI, ML and DL, Deep

Learning presents more flexibility in order to handle data compared to Machine Learning, but both do not need to be programmed. ML differentiates itself from AI in the sense that AI can be programmed in order to find solutions, so, and as seen in Figure 1.2, according to Russell and Norvig (2021), DL is a subfield of ML, that is also a subfield of AI.

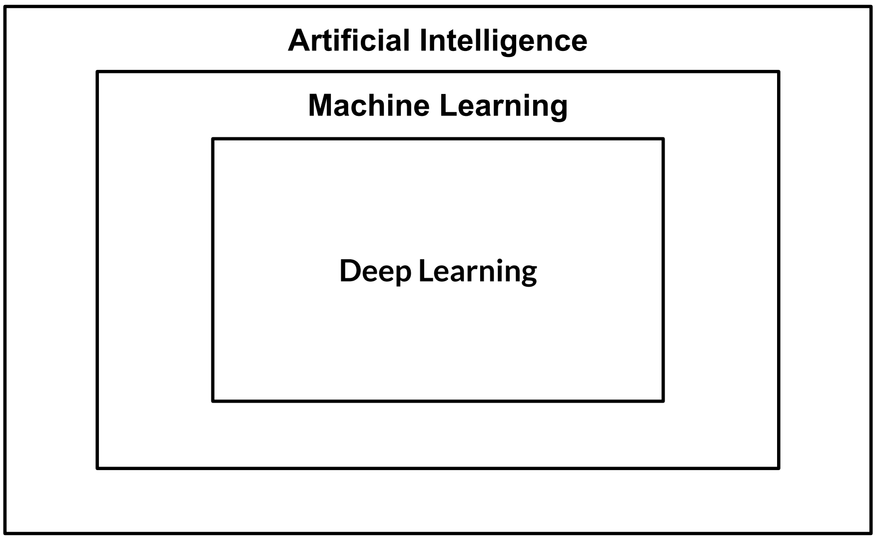

Figure 1.2 - Relation between AI, ML and DL (Adapted from Russell and Norvig, 2021)

According to Lazaridis et al. (2019) and Castillo (2021), Natural Language Processing (NLP) is a subfield of Artificial Intelligence that, with the help of ML, can process natural human languages. It can be used to read text or audio and video data and identify patterns. The necessity to do NLP came from the need of computers to communicate with humans, for artificial intelligence algorithms to learn from data written in natural language and to advance the scientific understanding of languages (Russell & Norvig, 2021). Parallel to the development of NLP and ML algorithms, concepts such as Neural Networks and Agents were developed and all can be used in order to implement AI algorithms (Castillo, 2021; Ruiz-Real et al., 2021).

1.4 - Additional AI applications and techniques

Additional AI concepts, such as NN, Big Data and Agents, were developed under the AI umbrella and complement other types of AI algorithms (Maheshwari, 2021). For example, and, according to Urbas (2020), Neural Networks (NN) can be seen as a computer architecture that is based on the biological brain and is different from conventional digital computers in the sense that computers work in a sequential way. This type of architecture uses simple processors that work in parallel and that communicate across the network. Two main types of neural networks exist, artificial and natural and both try to mimic the biological brain by breaking down a complex problem into smaller tasks that are able to be completed simultaneously.

According to Khodadadi et al. (2016), Internet of Things (IoT) systems are based on devices that are capable of connecting to the Internet. These devices are able to communicate with other entities at all times and between themselves. Some examples of this kind of devices are the smart devices that can be used in the household, sensors that read from the environment or every other electronic object that is aware of its context. IoT systems are connected to AI and ML systems in order to maximize resources for the creation of information. AI can be implemented in order to make decisions for the devices without any kind of human interaction (automated decision making) (Khodadadi et al., 2016).

Big Data is a concept that appeared with the World Wide Web's increased need to store larger amounts of data. This data can include images, video and speech and new algorithms were created for label identification (Russell & Norvig, 2021). According to Banko and Brukk (2001), with large enough data sets, an algorithm can achieve an accuracy of over 96%. According to Dewey (2019), it can be used, for example, to shift consumer preferences towards certain products, to better monitor the internet, or to increase a company's overall efficiency. This data can be divided in four ways, those being variety, volume, velocity and veracity.

According to Russell and Norvig (2021), a computer agent is an agent that is autonomous, can perceive its internal and external environment and can persist active over large periods of time in order to create and complete goals. According to the authors, an agent that achieves the best possible outcome is a rational agent. These agents can be applied in Fuzzy logic, that is a kind of logic that can represent any number between zero and one and aims to represent the human imprecision. Contrary to Boolean logic, which can only have two values, zero and one (representing true or false), fuzzy logic, due to its infinite choice possibility, allows for more flexible results.

This kind of logic can be used to construct inference models and deal with uncertain problems (Yang et al., 2020; Jafarian-Moghaddam, 2021). Fuzzy logic techniques can be used to control agents, improve their perception of the environment, and limit the number of possible outcomes in order to make decisions (Mostafa, 2018; Rahimova & Abdullayev, 2020). Russell and Norvig (2021) consider that rational agents are the basis of the standard model for AI and, in the case of complex systems, as it is not feasible for the agents to have perfect rationality, limited rationality, where agents take the best possible course of action, should be applied.

1.5 - Current state of Artificial Intelligence

Currently, Artificial Intelligence is being used in various industries with different purposes and objectives. In robotics, it is being used in self-driving cars and drones in order to reduce human interference in its usage (Vellinga, 2017). In this type of applications, AI algorithms try to understand the information gathered from the environment and with the help of sensors (IoT) and mimic the human decisions necessary for their handling. Some examples include a commercial robotic taxi service using self-driving vehicles, the use of drones in order to deliver blood across Rwanda, starting in 2016 (Russell and Norvig, 2021), the implementation of AI for partly driverless cars in Tesla and algorithms that evaluate driver's emotions while driving with Affectiva (Davenport et al., 2020).

Machine Learning algorithms have been used in Marketing, personalized recommendations across the internet and sales predictions. Generally, the ML algorithms will give recommendations based on past shopping experiences or browsing history and will relate them with other people with similar profiles, which work similarly to the algorithm applied by Amazon, for example (Martínez-López & Casillas, 2013; Russell and Norvig, 2021). Additionally, chatbots can take part in the sales process, allowing the augmentation of the sales team resources with the same number of employees (Singh et al., 2021). Machine Learning has also been used in spam reduction in emails, being nowadays in such email providers as Microsoft and Google (Oetjen, 2019).

Natural Language Processing (NLP) is being used in order to complete searches, process audio and video and translate them. Additionally, is it being used in statistics to analyze surveys and process CV's. Companies that use this technology includes Google, with *Google Search* and *Google Translate*, Apple, with its voice assistant *Siri* and Microsoft, using NLP in multiple departments, including Human Resources. Other technologies, such as Deep Learning or the Internet of Things are also used in conjunction with NLP (Aldabbas et al., 2020; Naqvi et al., 2020).

Other areas also use AI or AI-related technologies, such as the use of AI in Alibaba's City Brain project, by monitoring traffic and looking for accidents (Wired, 2018) with the objective to reduce the overall level of traffic in the city. Gaming is another area where ML and DL algorithms are present. *AlphaGo*, owned by Google is the first computer program to beat a professional player in the game *Go* (Russell and Norvig, 2021). Logistics also benefited from AI, allowing *JD.com* to fully automate its warehouse and Amazon to build a process system requiring no human intervention (Oetjen, 2019; Jaakoola, 2020; Gupta & Tripathi, 2020).

Chapter 2 - Rail Industry and Intermodal transportation

2.1 - Railway definition and evolution

According to Pyrgidis (2016), the railway is a terrestrial transport system that transfers both passengers and freight cargo from a starting point to an end destination. Trains move with the help of a guideway made of two parallel rails and are powered with the help of fossil traction, or remotely, by using electrical traction, although more types of train exist. Compared to other transportation methods, the implementation of train tracks is, on average, more expensive, but the average speed tends to be higher than, for example, maritime transport (Khaslavskaya, 2016). The railway infrastructure is constituted by the track where trains operate and auxiliary constructions (including, for example, tunnels and bridges), and other infrastructure necessary for the operation of trains, such as level crossings and stations. Rolling stock includes all the types of railway vehicles, that can either be powered or hauled. This includes locomotives, single railcars, trailer vehicles and maintenance vehicles (Brenna & Foiadelli, 2018; Flores & Pfaff, 2021).

According to Pyrgidis (2016) and Bersani et al. (2021), the railway operation includes all the activities involved in the railway transport. It can be divided into technical operations, such as scheduling and staffing, commercial operations, to assert the pricing policy, and maintenance operations, for all the equipment used. A railway track is the guideway for trains and is constituted by the two parallel rails over the sleepers (usually made of wood or cement) that are supported by the track bed (that includes the ballast). Locomotives (or traction units) hauls the trailer vehicles and as mentioned above, can be powered by, for example, diesel or electricity.

Single-rail cars are used for the transportation of passengers. Can include a driver’s cab on one/both ends or motor cars. A catenary (also named overhead catenary) is a cable that transmits electric power to, for example, locomotives or single-rail cars. A pantograph is a device mounted on the roof of an electric train that touches the overhead catenary in order to receive electric energy. A pantograph can be seen in non-electric trains, such as in inspection trains. A switch is a device used for a train to switch tracks and can be manual or remotely controlled (Pyrgidis, 2016; Zhang et al., 2018; Yin et al., 2020).

The history of the railway can be divided into five stages: the development of the wooden rails, steam power, electric power, diesel power and the development of high-speed trains. The earliest predecessor to the railway was presumed to be built in Ancient Greece around 600 BC and was used to carry boats in order to avoid sailing a much longer route. The next evolution of the railway came with the invention of funiculars, the first one being built in Austria in the 16th century. Posteriorly, wagon ways, pulled by horses, were put into use to transport mining equipment and coal and iron (Brenna & Foiadelli, 2018; Stacey, 2018).

According to Stacey (2018), the discovery of the steam engine by Watt in 1800 and the need to transport coal and iron from the mines were directly related to the development of the railway. In 1822, the first factory to assemble steam engines was opened by George Stephenson in England. Stephenson is considered the pioneer of the modern railway and, in 1830, the first commercial railway journey happened in England, between Liverpool and Manchester.

Although the first electric locomotives were built in Germany in 1879, electric traction appeared earlier with street tramways and mining railways, and it served as a complement to the mechanical system already in place. In the 20th century, the development of solid-state control systems and the consequent developments in signaling and control led to an increase in safety. Diesel appeared later in 1938 and is still currently in use, although is it being replaced with electric trains (Pyrgidis, 2016; Stacey, 2018; UIC, 2021).

The first commercial high-speed network appeared in 1964 in Japan, with a maximum speed of 210 Kmph. In Europe, the first high-speed trains appeared in the 1980s with the TGV reaching a maximum speed of 260 Kmph. Nowadays, commercial in-service high-speed trains can reach 350 Kmph. As it can be seen in Table 2.1, China is the country that has the biggest high-speed rail network, at 16,293 km whilst having a maximum speed of 300 Kmph (Pyrgidis, 2016).

Table 2.1 - Top 5 countries with the longest high-speed rail networks (Pyrgidis, 2016)

Order	Country	Length (Km)	Maximum Speed (Km)
1	China	16,293	300
2	Spain	2,427	310
3	Japan	2,346	320
4	France	1,906	320
5	Italy	959	300

The proliferation of high-speed rail networks led to the need of higher network capacity and consequently led to the development of different AI algorithms and uses. The railway sector has been using AI technologies such as ML algorithms, for a vast number of different areas such as train scheduling (Zhang et al., 2018), including train path allocation and traffic management, predictive maintenance (Liu et al., 2019; Estil-Les et al., 2020), of both the rolling stock and infrastructure and operations, such as sales prediction, chatbots for passenger assistant, terrorism prevention, passenger flow through stations and abandoned luggage detection (Yin et al., 2020; UIC, 2021).

2.2 - Train scheduling

The Train Scheduling (TS) problem is a complex and hard problem with often no optimal solution and depends on the characteristics of the rail network, such as how connected the network is, how many tracks exist or what type of trains with different priorities need routing (Sanhueza, 2021). According to Estil-Les et al. (2020), passenger trains in most corridors use a clockface timetable (a type of timetable more easily memorized by the user) where trains run at regular intervals, at least during the peak hours. Currently, the clockface timetable is also being implemented with multiple lines and services, where coordination should exist between trains that operate on main corridors and the other feeding trains. Additionally, transfers and correspondence between branches and junctions should happen in this kind of systems.

Freight trains differ from passenger trains in the lack of need for a fixed timetable. Instead, trains usually only depart when the load of the train reaches a weight target and operate with no predetermined route in an ad-hoc way. Lambropoulos mentions that a trend exists to consider freight trains as passenger trains in respect to their scheduling (Pyrgidis 2016). In order to try and solve the TS problem, a number of algorithms have been created, and, in order to deal with the constraints of railway scheduling, some use AI algorithms, such the ones based on Fuzzy systems (Pyrgidis 2016).

Estil-les et al. (2021) divide the TS problem into three different types of solutions: classic, where a timetable is created for high or medium speed trains; real-time, where the current position of trains is known and a dynamic solution is made when problems arise, and robust, that takes into account delays and controls the distance between two consecutive trains. Li et al. (2020) use a tabu search algorithm that optimizes total train travel time in freight trains by using a flexible timetable without a fixed departure and arrival time but a portion of a timetable. It also takes into account car flow transfer between trains and some additional time constraints.

According to Jafarian-Moghaddam (2021), one of the most important variables in order to solve both the TS problem and energy consumption problems is speed. The author mentions some advantages of increasing speed, such as an increase in punctuality, railroad capacity and the stakeholder's satisfaction. Some disadvantages include the high energy consumption and, consequently, an increase in costs and pollutant emissions. A new model is proposed using fuzzy logic, integrating both macro and micro levels, featuring almost no need for input parameters and taking into account resistance and tractive force of the trains. This model is based on the concept of economic speed, by trading off speed for the other constraints already mentioned.

Another model was proposed by Estil-les et al. (2020), where the authors introduced a model for the optimization of high-speed train scheduling. The limitations of this model are that the approach focuses only on high-speed trains and it accounts only for passenger demand, train capacity and train priority (this priority can usually be interpreted as different train services). Additionally, it includes the train rescheduling problem where, in order to minimize consequences, the train with the greater occupancy has priority over the other trains. This model works on a micro level with the railway signal control system working on each track section.

The Min-Max approach was proposed by the same authors, where it is mentioned that the train scheduling will shift from a static timetable to a more dynamic type where the timetable can be modified according to passenger's demands. The Min-Max algorithm is based on graphs where each pair of nodes represents the arrivals and departures of each train. It also takes into account rescheduling and other constraints while keeping the flexibility needed to match customer demands to the availability of the trains themselves (Estil-les et al., 2021).

Sanhueza et al. (2020) focuses on a more specialized type of rail network, that is exclusive to mines in Australia. A genetic algorithm that assigns a train speed for each network section is used with the objective of reducing total travel times and takes into account the size of the fleet This type of algorithm allows for a more flexible schedule, as there is no need for a fixed timetable. Some other algorithms (Table 2.2) were proposed that take into account one or more constraints or use a different approach to the algorithms already discussed.

Table 2.2 – Algorithms used in train scheduling and corresponding references (Li et al., 2020; Jafarian-Moghaddam, 2021)

Model	Reference
General models that had the objective of reducing travel time, energy consumption and increasing satisfaction of passengers and goods.	Albrecht et al. (2016); Scheepmaker et al. (2017); Yin et al. (2017)
Graph approach	Liebchen & Stiller (2010)
Heuristic and meta-heuristic algorithms	Cacchiani, et al. (2016); Cacchiani and Toth (2012); Zhang et al. (2019)
Branch-and-bound methods	Yang (2009)
Column generation	Cacchiani et al. (2008)
Constraint generation	Odijk (1996)
Stochastic and fuzzy approaches	Yaghini et al. (2015); Yang et al. (2014); Chow & Li (2014)

The generic models proposed in Table 2.2 do not focus on a specific algorithm but instead focus on solving multiple constrains and limitations of the rail network whilst trying to increase, for example, passenger satisfaction or energy consumption. Other models proposed included using a graph algorithm (Liebchen, 2008), and other heuristic or non-heuristic algorithms or different approaches for flexible scheduling generation (Li et al., 2020; Jafarian-Moghaddam, 2021). ML algorithms are not only applied to train scheduling, as UIC (2021) proposes that the same approach can be taken into maintenance and inter modal networks.

2.3 - Other uses of AI in the industry and intermodal transportation

Artificial Intelligence algorithms have not only been developed for rail infrastructure, as these kinds of algorithms can decrease rolling stock maintenance and inspection costs and be applied in order to improve performance in inter modal transport nodes. This type of maintenance has been done manually, where railway personnel inspect each individual component, such as bogies or engines (UIC, 2021). Kishore and Prasad (2016) proposed an idea to use image detection with a wide-angle camera in order to inspect bogies and distinguish the defective parts from the non-defective ones. According to the authors, having inspectors look at bogies with trains moving at 30 Kmph raises reliability and safety questions.

Uno et al. (2020) created a system to inspect the side of the underfloor of trains, that includes the inspection of deformations, loose bolts, or cover handles. This system works in trains running at less than 25 Kmph and is composed of a camera, projector, processor, terminal, and detectors. Liu et al. (2019) summarized the development of visual inspection technology, both for rolling stock and rail infrastructure, where the authors applied this method of inspection to rail track, including the surface, component deformation, identification, and extraction; catenary; train components, such as wheels; train tail signs and other infrastructure.

Predictive maintenance on infrastructure contributes to the punctuality and safety of trains. According to UIC (2021), replacing manual patrols and periodic manual inspections with more frequent automated inspections contributes to the availability, reliability, and safety of the railway network. Elleuch et al. (2020) focused on geometric failures on the railway track by presenting a system that forecasts its deterioration. This model is based on a variable neighborhood programming heuristic using automatic programming, and has a learning stage, that uses the data available up to the present, and the testing phase, where it is implemented.

According to UIC (2021), AI technologies, such as big data algorithms, blockchain or virtual reality are hard to deploy to the real world due to need for lower latency and higher speeds. 5G connectivity can help to solve this problem by offering 20Gbps and 10Gbps of download and upload respectively and a latency of 1ms. The authors present three main scenarios for the 5G use in rail: automatic train operation, intelligent dispatching, and intelligent maintenance. According to the authors, the use of 5G can be applied to high-speed and autonomous trains, as 5G has an advance over conventional train telecommunication network in connection speeds, lower latency and less tower transfer time.

The use of AI in other railway operational areas and the development of both rolling stock and rail infrastructure is being implemented in, for example, autonomous and high-speed rail networks (UIC, 2021). In high-speed rail networks, the definition of the minimum speed of a train track (or the maximum speed of a train) to be considered high-speed is not explicit. Initially, it was considered to be 200 Kmph and, nowadays, according to the Trans-European High-Speed Network lines, it is considered to be 250 Kmph if the track is new or 200 Kmph in existing tracks that went through modernization (Pyrgidis, 2021). Compared to normal trains, artificial intelligent can also be used with high-speed trains in some areas (Yin et al., 2020) such as smart planning, including train timetables, rolling stock planning, crew scheduling and knowledge-based customer service; intelligent control, such as speed and trajectory control, intelligent equipment, intelligent maintenance, data mining and computer vision.

Yang and Zhao (2019) proposed that, in order to use free space not occupied by passengers in high-speed trains, the remaining space could transport freight. According to the authors, although the amount of freight that can be shipped is low, the transportation demand is high, and it could increase profits in high-speed rail operations. Using the optimization theory and nonlinear programming, a model was proposed to increase the maximum profits of high-speed rail operators.

Autonomous or driverless trains are expected to address the growing demand for both passengers and freight cargo and decrease safety issues resulting of human error. In addition to some driverless systems of low to medium transport capacity (cable or self-propelled), driverless trains are also present in metro systems and can be classified into four different categories (Pyrgidis, 2016; Singh et al., 2021): trains that operate with a driver and only include Automatic Train Protection (ATP); semi-automatic trains that operate with a driver, but only operate in case of emergency; driverless trains, that do not have a driver, but a train attendant that opens and closes doors and also acts in case of emergency, and finally unattended trains, that have no driver or attendant at all.

According to Singh et al. (2021), some other advantages of autonomous trains include a decrease of environmental problems, roadway congestion or, together with autonomous vehicles, better accessibility and land use improvements. The IoT technology allows for communication in locations where there is a possibility that trains might be considered a problem with pedestrians or vehicles, such as rail crossings. AI technologies, such as natural language processing, Machine Learning, vision and speech processing, expert systems and the IoT framework already mentioned allow the optimization of the railway network system (Singh et al., 2021).

According to Fraga-Lamas et al. (2017) and Singh et al. (2021), due to the low share of freight cargo transport through rail, particularly in the case of freight that goes through intermodal terminals, additional measures are needed on top of train automation in order to increase that share. Artificial Intelligence technologies can also be used on railway operations, specifically in the technical and commercial operations (UIC, 2021). In the fight against terrorism, face recognition is being used in order to identify passengers before boarding a train or passengers going through customs (Global Times, 2017; RFI, 2017). In order to implement this, Machine Learning has been used to do this image analysis.

Virtual assistants and chatbots are used in order to make reservations and book passenger tickets. Virtual assistants can replace humans in customer service. These virtual assistants use Natural Language Processing in order to recognize speech of multiple languages and can avoid customer claims if the meaning of words from customers can be correctly interpreted (UIC, 2021). Sales predictions can be predicted using big data algorithms in order to learn from past tickets sold and make more accurate predictions. (Towards Data Science, 2018; Jaakkola, 2020; UIC, 2021).

2.4 - Other intermodal transportation applications

The focus of the application of Intelligent Systems to transport has been mostly focused on unimodal problems. Intermodal transportation is when, in order to reach the destination, a switch between at least one mode of transportation happens. Intermodal freight transport is the combination of at least two different modes of transportation that use the same container for goods or, in the case of intermodal passenger transport, when passengers connect between more than one type of transport in order to reach their destination (Pyrgidis 2016). According to Baykasoğlu et al. (2018), intermodal algorithms are complex and differ in structure, characteristics, and solutions from unimodal transportation systems, and the authors additionally mention the lack of algorithms that tackle multiple problems and most only focus on one, such as fleet planning or fleet sizing and routing (Catania et al., 2015; Eskandari & Mahmoodi, 2016).

When focusing on freight intermodal transportation, SteadieSeif et al. (2013) mention that the use of more than one type of transport to haul freight cargo can result in a more efficient and sustainable operation and where the planning should be carefully prepared in order to achieve the desirable operation. The authors also mention that the use of containers has been growing and can achieve the standardization of cargo transportation across more types of transport. Similar concepts to freight intermodal transportation also appeared along the years, such as multimodal, co-modal or synchromodal freight transportation but, according to the United Nations Economic Commission for Europe [UNECE] (2009) and the European Comission [EC] (2006) these concepts differ, where multimodal transportation can be defined as the transportation between more than one mode of transport, co-modal as an improvement in the efficiency and sustainability of the transportation and lastly synchromodal transportation can be defined as an evolution to intermodal transportation, where the choice of transport mode can be made independently of the company the cargo originates from.

Passenger intermodal transportation allows for a more flexible and efficient way for passengers to travel and allows for companies in the transport industry to implement systems capable of dealing with multiple ticketing standards or infrastructure, such as terminals, allowing for a better customer experience (Albalate et al., 2015). One of these examples and, as mentioned by the authors, HSR feeding into long haul air flights can allow a reduction in air pollution and a reduction in flight delays.

Maity et al. (2019) created a model using a neutral network and linear programming that tries to solve problems present in intermodal nodes. The authors refer that there are multiple objectives for the intermodal transport problem, including a decrease in total transportation time, reduction of overcrowding on infrastructure equipment's and to reduce energy consumption, for example. A fuzzy approach has also been studied by Yang et al. (2020), where the authors mention that a system's reliability can be compromised in case some of the nodes of the intermodal system fail, specifically in a rail-road system. With these rail-road types of systems, additionally, a tabu algorithm was also used in order to try and solve it.

Artificial Intelligence has been evolving from a theoretical field of study to having real world applications that can be applied into different industries. Subfields of AI such as Machine Learning or Deep Learning allowed for a more flexible and dynamic implementation of AI and the use of multi agents and fuzzy logic can provide the reduction of costs and improvement in performance of different businesses, as is the case of the rail industry (Russell & Norvig, 2021; Pyrgidis, 2021). Multiple algorithms have been proposed in order to solve the TS problem and train maintenance and inter modality can also benefit from these algorithms that can be applied for both conventional, high-speed and autonomous trains. The operational area of the rail industry can also benefit from the implementation of AI techniques, such as its use in virtual assistants and chatbots and to make sales predictions. One of the challenges that intermodal transportation systems have is that they mostly focus on one problem and AI algorithms have tried to solve it using a multitude of different approaches.

Chapter 3 - Theoretical Approach

In the previous chapter, a deeper understanding of the two main topics present in this thesis was discussed in the literature review and, consequently, led to the proposal of three different research questions related to two main objectives. The first objective, the possibility to implement AI in the rail industry, includes an analysis of the sociodemographic differences on the knowledge of AI and a broader view of the benefits, risks, trust that might affect the different areas of the rail industry, including not only the core areas of the industry, but also secondary and auxiliary tasks and operations.

Regarding this first objective, the study of the *possibility of implementing AI on the rail industry*, the relation between the topics of AI and the rail industry is already being investigated and AI technologies are already being implemented in the rail industry (Shaw et al., 2019; Yang et al., 2020). The study of AI not only encapsulates the study of its techniques, algorithms, and technologies, but also of its subfields, such as Machine or Deep Learning and can additionally work with non-AI technologies. The rail industry is not the only area where the implementation of AI is being studied, as in other areas, such as Medicine, Computer Engineering or Marketing (Russell and Norvig, 2021).

The creation of rail-based commercial transport systems happened in the 19th century and, since then, the multiple developments (that can include, for example, high-speed and autonomous trains or train path allocation and scheduling algorithms) that followed it led to a deeper investigation of how to solve the different problems that arose from these new developments (Hintjens et al., 2020). Multiple solutions were proposed and, with accordance to the objectives being investigated, the research questions proposed below reflect how a new disruptive technology such as Artificial Intelligence can tackle these problems whilst taking into consideration both the positive and negative implications of its implementation.

In order to study the impact that Artificial Intelligence has on the implementation of systems with this technology in the rail industry, two research questions were proposed.

Research Question 1: How do sociodemographic factors influence the knowledge about AI in the rail industry?

Although AI is a technology that was created in the 1950's, until the 21st century only the theoretical foundations were laid and projects external to the academic world were scarce. Since the beginning of the century, projects have started being implemented in companies with various degrees of success and their implementation was mostly a focus of the Research and Development's (R&D) internal division of the companies (Haenlein & Kaplan, 2019). Due to these recent developments, the knowledge of AI and its algorithms might vary, and this research question aims to distinguish the sociodemographic characteristics that may impact their knowledge about Artificial Intelligence in the rail industry.

Research Question 2: What is the possibility to implement AI in the rail industry?

When considering the implementation of AI technologies, the factors that can impact its implementation need to be considered. Broader factors, such as AI perception, economic value, ethics or risks need to be related to each AI solution proposed. Makridakis (2017) mentions that these types of factors need to be studied before the implementation of AI but that, if applied correctly, AI can bring a competitive advantage to companies while diminishing certain risks that were traditionally associated with the technology (Russell and Norvig, 2021). The research questions focus both on the problems that appear in the different areas of the rail industry and what are the factors that might affect them. To expand the scope of the investigation outside the rail industry and additionally, to be able to study not only the impact of AI in the rail industry, a third and final research question is proposed related to intermodal transportation.

Research Question 3: What is the possibility to implement AI in the intermodal transportation?

By studying the implementation of AI in the rail industry alone, even if it includes the rail infrastructure, the trains and the core and auxiliary operations, some external aspects of the environment should be considered. One of these externalities is that both passengers and freight cargo can start or end in a train but switch to or from a different type of transportation, either independently or integrated in, for example, in an intermodal terminal. According to Dong et al. (2018) and Filina-Dawidowicz et al. (2020), there is still a difficulty in integrating these independent systems into a single and integrated one with algorithms capable of improving the overall efficiency. The third research question, of the study of the possibility to implement AI in intermodal transportation, aims to, in a similar structure to the second research question, study the impacts that AI can bring to this kind of systems, algorithms and operation.

Chapter 4 - Methodology

4.1 - Research Model

With the definition of the research questions related to the main objectives of this thesis, the formulation of hypothesis that connect to these research questions is essential in order to collect the necessary information to make conclusions. This investigation process is based on research done about the topic being studied and is based on the method of science, where in order to acquire knowledge, a formulation of questions occur that represent the problems trying to be answered. In order to find these solutions, a scrutiny needs to happen based on empirical evidence and following steps that include "Observation, measurement, verification, and evaluation." (Thomas, 2021, p. 4).

In the research process, a number of formal approaches exist, and those approaches can additionally be classified differently according to the stage of the investigation. When starting the investigation process, an exploratory research approach was followed to review the literature related to the impact of AI in the rail industry and allowed for a hypothesis formulation based on these topics (Gower, 1997 and Marder, 2011). In order to gather the necessary data for this investigation, both primary and secondary collection procedures were used, with the use of a quantitative approach-based questionnaire, that will be explained in detail in this chapter, for the primary data, and a collection of articles, books, websites and similar data sources constituted the secondary data collection sources. In order to present the most recent and reliable data, only articles that were five or less years old were chosen to complement the AI literature and with the concern of only choosing articles from reliable journals.

When talking about the scientific and investigation methods, an inductive method type of investigation will be followed, where, in order to investigate our theory and the general objectives in question, hypothesis will be formulated according to the research questions and relations and comparisons will tried to be reached (Freixo, 2012). To collect the data, a choice between two sample methods were presented, probability sampling and non-probability sampling. A non-probability sampling method was used, in particular using a convenience, non-probability sample, not representative of the population, where the sampling error might be difficult to measure but with the advantage of being a swift and convenient way to gather the data (Thomas, 2021).

To collect and gather the data necessary for the investigation, between the option to follow a quantitative, qualitative or mixed approach, a quantitative-only approach was chosen, as it presents itself as being more controlled, using numerical data and allows for the statistical analysis by using independent variables and analyzing their relation to the dependent variables, which fits the model based on the formulation of hypothesis, allows for the use of a surveys and to conduct descriptive and analytical statistics (Wienclaw, 2021).

As seen in Figure 4.1, this thesis follows the normal structure of a dissertation and its three main stages of investigation. In order to begin the investigation, a literature review was conducted based on Artificial Intelligence and the Rail industry. In virtue of the choice to use a quantitative-only approach, a collection of data done using individual questionnaires with a previous approval by the supervisor was conducted, and, posteriorly, a verification and statistical analysis stage happened, as explained in detail in the next section.

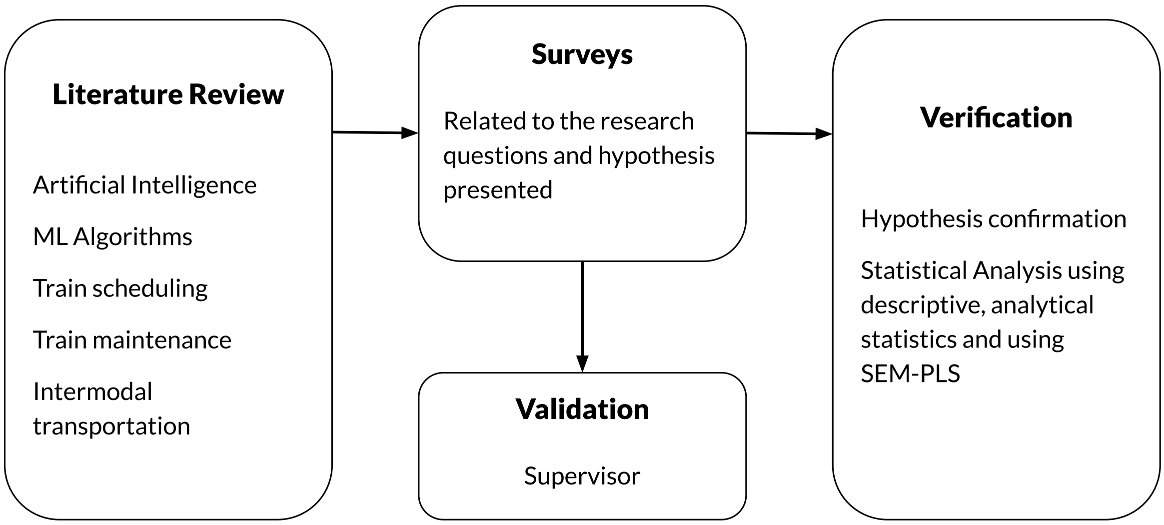

Figure 4.1 – Investigational Model of the thesis

To create and validate the surveys, the research questions and hypothesis formulated are based on the first step related to the literature review. Regarding the surveys, they were distributed through social networks and by e-mail, and a total of 101 and 106 answers were collected between the 4th and the 15th of January of 2022, for each of the surveys present in Annex A and Annex B, respectively. In order to formulate this hypothesis and to create the questions for both of the surveys, Table 4.1 and Table 4.2 present the two objectives of this thesis, along with the respective research questions, the methodology, including the data collection and data analysis methods and the associated literature review.

Table 4.1 - Relation between the first objective, research question, methodology, and respective references

Objective	Research Questions	Hypotheses	Methodology	References
Objective 1 – The possibility of implementing AI in the rail industry	RQ1 – How do sociodemographic factors influence the knowledge about AI in the rail industry?	*The sociodemographic differences influence the knowledge of AI in the rail industry*	Quantitative - Descriptive and Analytical Statistics [Survey A]	Haenlein and Kaplan (2019), Russell and Norvig (2021), Horowitz & Kahn (2021)
	RQ2 – What is the possibility to implement AI in the rail industry?	*The benefits of AI have a positive impact on the possibility to implement AI in the rail industry*	Quantitative - SEM-PLS [Survey A]	Martínez-López and Casillas (2013), Costa (2020), Lim et al. (2020), Yang et al. (2020), Damioli et al. (2021), Russell and Norvig (2021), Lee et al. (2021), Gil et al. (2021), Gupta et al. (2021), Qu et al. (2021)
		The risks of AI have a positive impact on the possibility to implement AI in the rail industry		Harari (2015), Shaw et al. (2019), Jordan (2020), Ryan (2020), Yang (2020), Russell and Norvig (2021), Berente et al. (2021), Saßmannshausen et al. (2021); Woodcock et al. (2021)
		The trust in AI has a positive impact on the possibility to implement AI in the rail industry		Wonglakorn et al. (2021)

Table 4.2 - Relation between the first objective, research question, methodology, and respective references

Objective	Research Questions	Hypotheses	Methodology	References
Objective 2 – The possibility of implementing AI in intermodal transportation	RQ3 – What is the possibility to implement AI in the intermodal transportation?	*The benefits of AI have a positive impact on the possibility to implement AI in the intermodal transportation*	Quantitative – SEM-PLS [Survey B]	de Abreu e Silva & Bazrafshan (2013), Pfoser et al. (2016), Bahtizin et al. (2019), Balster et al. (2020), European Union (EU) (2019), Singh et al. (2021)
		The risks of AI have a positive impact on the possibility to implement AI in intermodal transportation		Givoni & Banister (2006), Janic (2007), Nair et al. (2010), Iannone (2012), Ishfaq & Sox (2012), Barker (2016), Wang et al. (2017), Dong et al. (2018), Filina-Dawidowicz et al. (2020), Hintjens et al. (2020), Zhang & Li (2020), Lorenc & Kuźnar (2021)
		The trust in AI has a positive impact on the possibility to implement AI in intermodal transportation		Gambardella et al. (1998), Horowitz & Kahn (2021)
		The awareness in AI has a positive impact on the possibility to implement AI in the intermodal transportation		Rusca et al. (2019), Wonglakorn et al. (2021)

4.2 - Data Analysis Tools

As previously mentioned, posterior to the literature review, the collection of the data was made using two surveys, a choice that was made based on the decision to follow a quantitative-based approach. The use of questionnaires allows for the collection of data in order to assess opinions, attitudes or prevalence of a subject in a quantifiable way, and, posteriorly, to make statistical research and allows to reach conclusions. Of the tree main types of questions that exist, closed, semi-closed and open-questions, due to the tools used to make the already mentioned statistical studies, the questionnaire will feature only closed-questions, specifically using a 5-point *Likert* scale (Likert, 1932).

The first approach used involved the use of descriptive and analytical statistics, that, according to Saunders et al. (2019) can be used to order, classify and relate numerical variables by using a statistical approach with the objective to quantify results. An analysis of the means, medians, standard deviation, kurtosis and skewness was conducted and allows to present the general results related to the first three questions from the first survey. To further examine the data, analytical statistics were used, by conducting analysis of variances (ANOVA) and comparison tests. To conduct the tests and show the necessary charts, the Python and R programming languages were used with the help of the *SciPy*, *bioinfokit* and *ggpubr* code libraries.

The second approach used a *Structural Equations Modelling* (SEM) analysis, a path analysis modelling tool, as it allows to use to do a statistical analysis through the study of the relation between dependent and independent variables. SEM is a type of confirmatory method that provides a practical approach to theory testing and development and can be explained as the relation between multiple regression and factor analysis (Anderson and Gerbing, 1988). It is also known as *Latent Variable Analysis*, as SEM tries to explain the dependence relation between latent variables and is used to analyze consumer behavior and comparative predictive research (Sarstedt et al., 2017; Rigdon, 2016).

Partial Least Squares (PLS) approach is an example of a variance-based approach of SEM and was the approach that was used in this thesis in order to analyze two RQ (Hair et al., 2017). The use of PLS allows for the use of smaller samples than when using SEM, offers a more flexible way to measure the relations between variables and can analyze formative indicators (Shackman, 2013). In order to do the statistical analysis of the survey data, the next subchapter presents the conceptual model, including the hypothesis and the direct effects and, with the help of the *SmartPLS 3 software*, the hypothesis will be tested in the following chapter.

4.3 - Conceptual Models

4.3.1 - RQ2 - What is the possibility to implement AI in the rail industry?

Hypothesis formulated based on the research questions for the second RQ:

H1a – The benefits associated to the implementation of AI in the rail industry positively impact the possibility to implement AI in the rail industry

H1b – The benefits associated to the implementation of AI in the rail industry positively impact the trust in AI in the rail industry.

H2 – The risks associated to the implementation of AI in the rail industry positively impact the possibility to implement AI in the rail industry

H3a – The trust of AI in the rail industry positively impacts the possibility to implement AI in the rail industry

H3b – The trust in AI in the rail industry mediates between the benefits of AI in the rail industry and the possibility to implement AI in the rail industry

H3c – The trust in AI in the rail industry mediates between the risks of AI in the rail industry and the possibility to implement AI in the rail industry

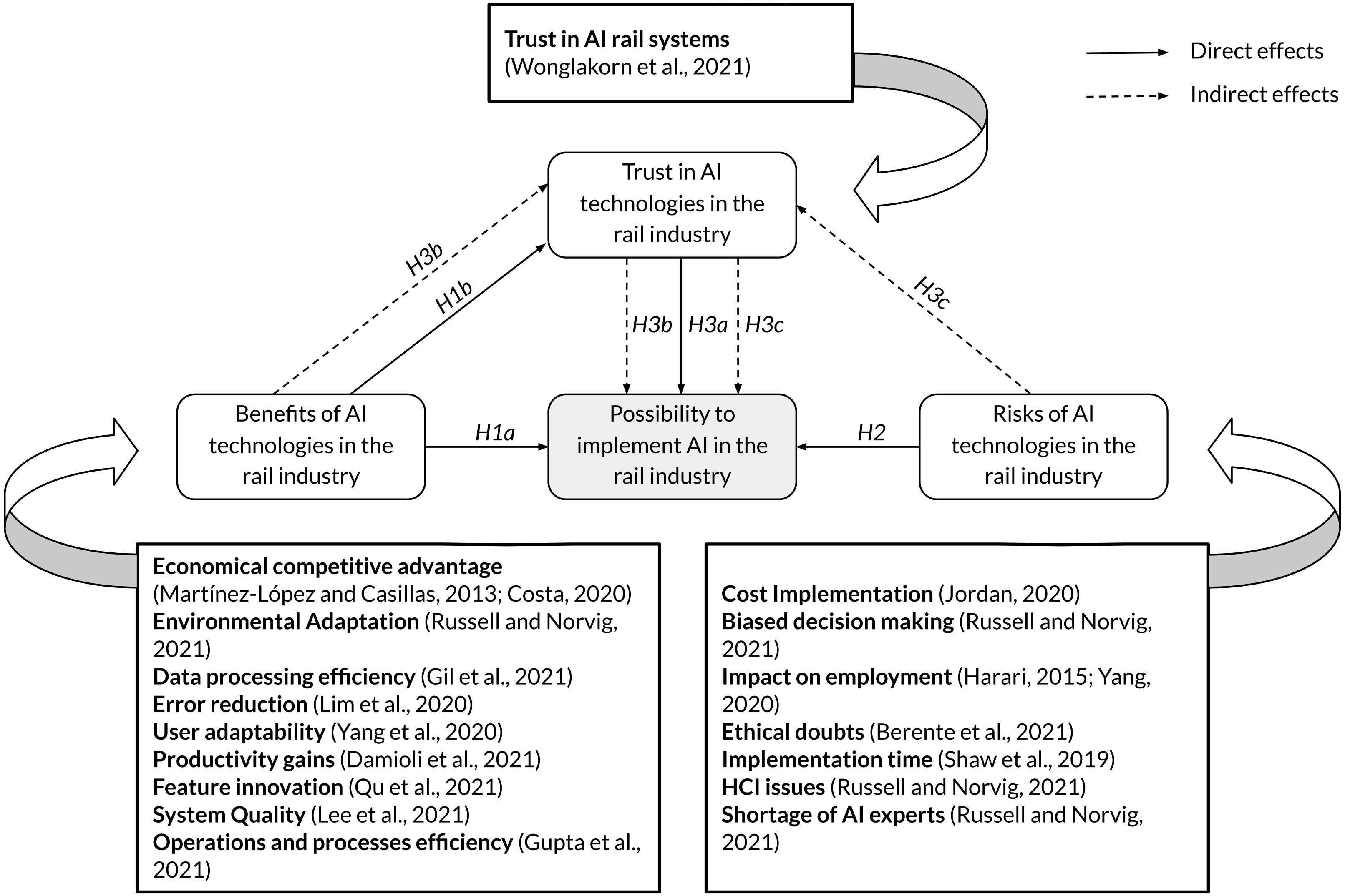

Figure 4.2 - Conceptual Model and Hypothesis for the first SEM-PLS analysis

4.3.2 - RQ3 – What is the possibility to implement AI in the intermodal transportation?

Hypothesis formulated based on the research questions for the third RQ:

H1a – The benefits associated to the implementation of AI in intermodal transportation positively impact the possibility to implement AI in intermodal transportation

H1b – The benefits associated to the implementation of AI in intermodal transportation positively impact the awareness in AI in intermodal transportation

H1c – The benefits associated to the implementation of AI in intermodal transportation positively impact the trust in AI in intermodal transportation

H2a – The risks associated to the implementation of AI in intermodal transportation positively impact the possibility to implement AI in intermodal transportation

H2b – The risks associated to the implementation of AI in intermodal transportation positively impact the trust of AI in intermodal transportation

H3a – The trust of AI in intermodal transportation positively impacts the possibility to implement AI in intermodal transportation

H3b – The trust of AI in intermodal transportation mediates between the benefits of AI in intermodal transportation and the possibility to implement AI in intermodal transportation

H4a – The awareness associated to the implementation of AI in intermodal transportation positively impact the possibility to implement AI in the intermodal transportation

H4b – The awareness of AI in intermodal transportation mediates between the benefits of AI in intermodal transportation and the possibility to implement AI in intermodal transportation

H4c – The awareness of AI in intermodal transportation mediates between the risks of AI in intermodal transportation and the possibility to implement AI in intermodal transportation

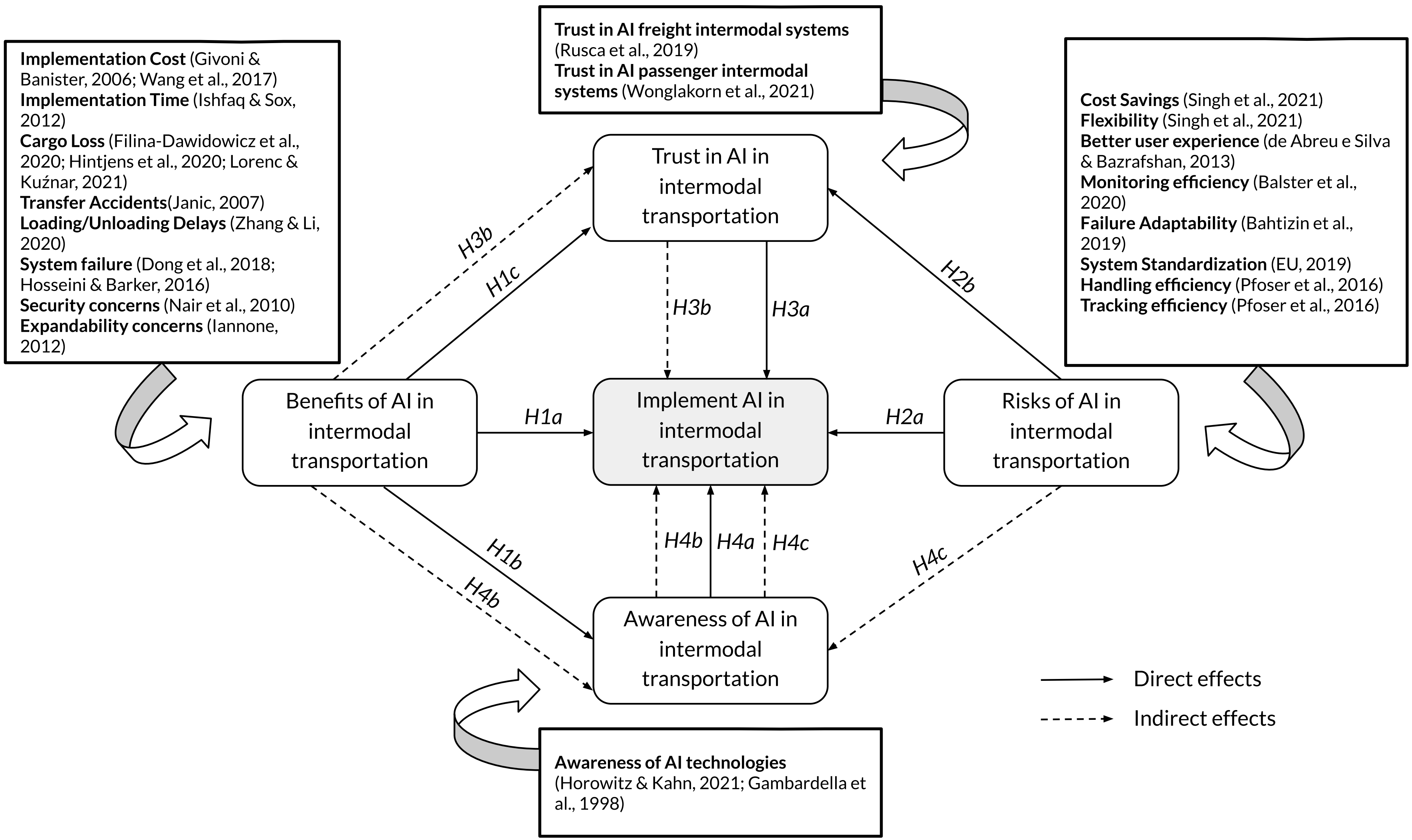

Figure 4.3 - Conceptual Model and Hypothesis for the second SEM-PLS analysis

4.4 - Sample Characterization

In order to proceed with the data discussion, firstly an analysis of the sample was done in order to assert the validity of the heterogeneity of the survey. At the end of the questionnaire, the age, sex, country and years of experience in the area was asked in order to understand the demographics, knowledge and experience in the area. Despite the nature of this sociodemographic questions, the surveys were fully anonymous and beforehand, tests were conducted with the help of four experts in the area that provided feedback about the questions to be asked and the general structure of the survey.

4.4.1 - Survey A – The impact of AI in the rail industry

Regarding this first survey, the sample included 101 individuals. When analyzing the gender distribution, we can see that 79 (78%) identified as Masculine, 21 (21%) identified as Feminine and 1 (1%) identified as Other.

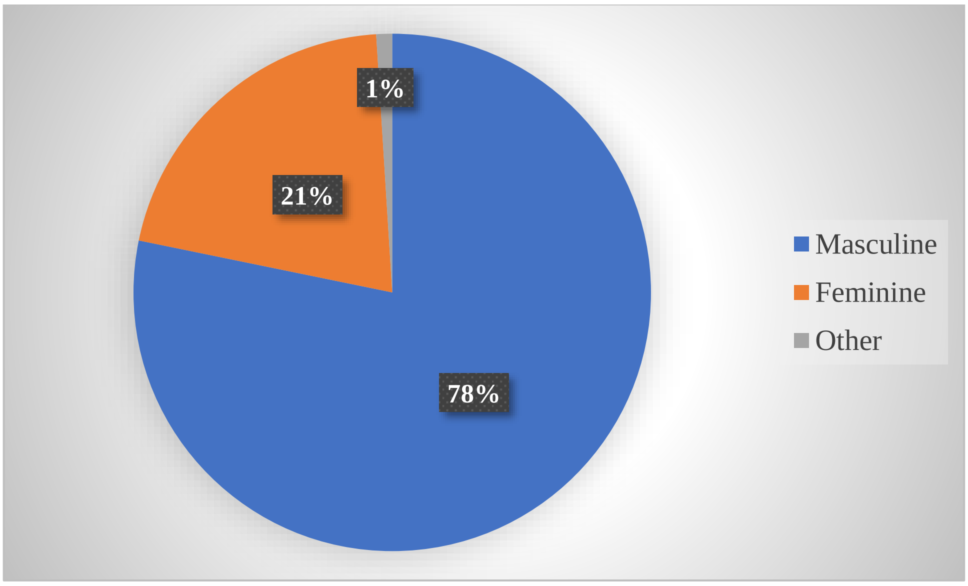

Figure 4.4 – Survey A's Gender Distribution

Regarding the age, 38 (39%) respondents were between 18 and 25 years old, additionally 38 individuals were between 26 and 35 years old (39%) and lastly 22 (22%) were between 36 and 50 years old.

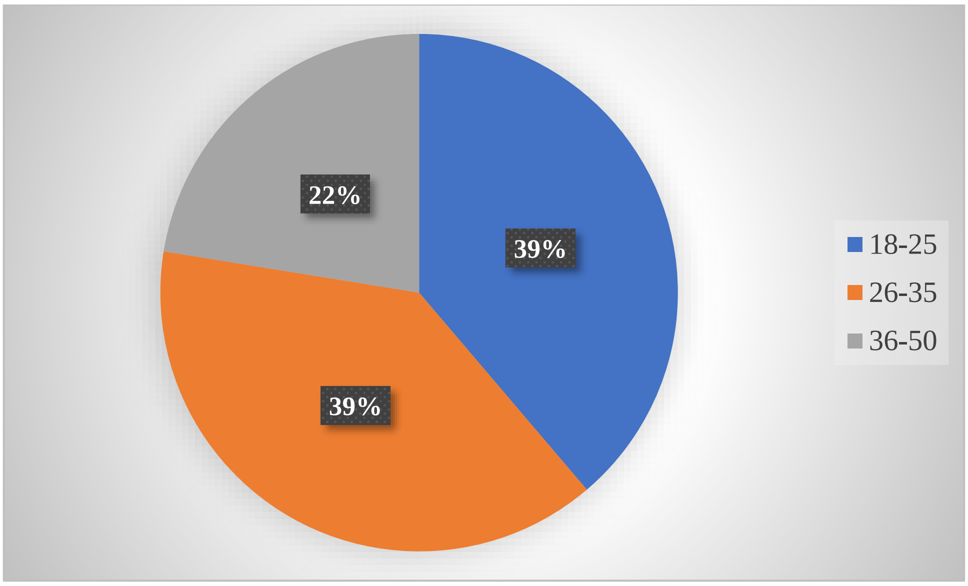

Figure 4.5 – Survey A’s Gender Distribution

Regarding the education level, 1 (1%) finished Elementary School, 1 (1%) finished Intermediate School, 9 (9%) completed High School, 68 (67%) had an undergraduate degree, 21 (21%) had a master’s degree and lastly 1 (1%) had a PhD.

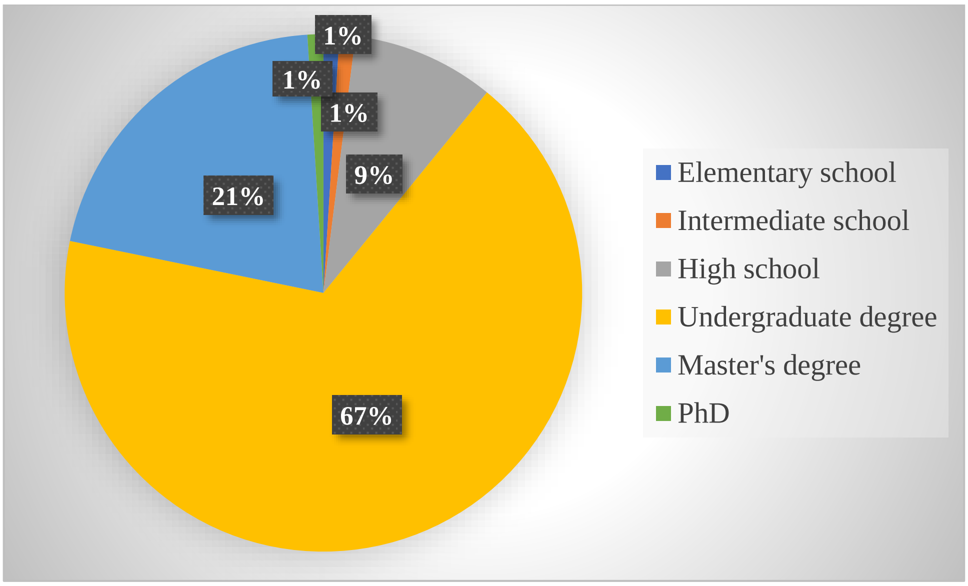

Figure 4.6 – Survey A’s Education Level

Regarding the years of experience in the area, 19 (19%) had less than 1 years’ experience in the area, 23 (23%) had between 1 and 2 years’ experience in the area, 33 (32%) had between 3 and 5 years’ experience in the area, 9 (9%) had between 6 and 10 years and finally 17 (17%) respondents had more than ten years’ experience in the area.

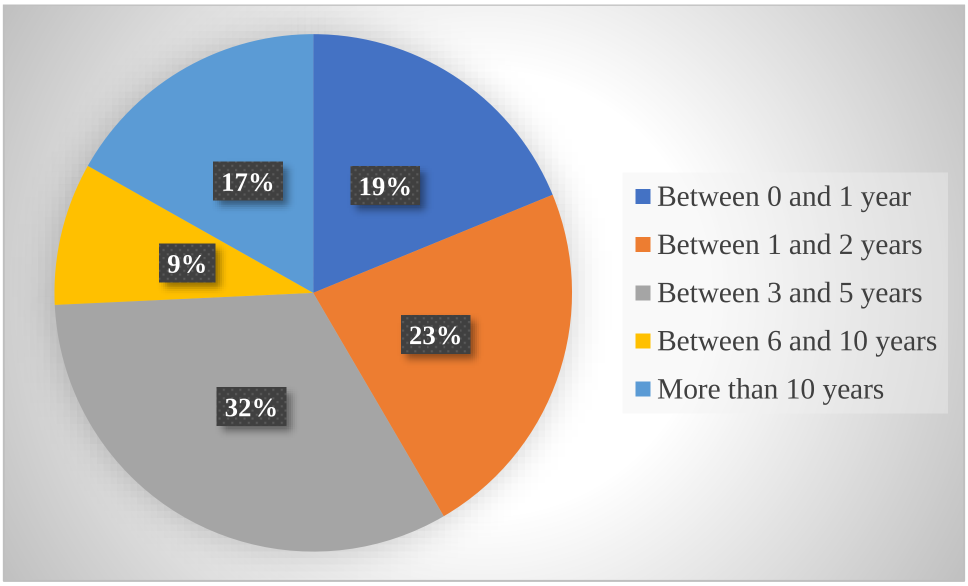

Figure 4.7 – Survey A's Years of Experience in the area

Regarding the nationality, the Table 4.3 - Survey A respondents' Countries shows that 60 (60%) of the respondents were from the United States of America, 14 (14%) were from India, 5 (5%) from Portugal, another 5 (5 %) from Canada, 4 (4%) from Australia, 2 (2%) from the United Kingdom and 11 countries with 1 (1%) individual each.

Table 4.3 - Survey A respondents' Countries

Country	Number of Respondent's	% of Respondent's
Angola	1	1%
Argentina	1	1%
Armenia	1	1%
Australia	4	4%
Austria	1	1%
Barbados	1	1%
Belarus	1	1%
Bosnia and Herzegovina	1	1%
Canada	5	5%
Germany	1	1%
India	14	14%
Netherlands	1	1%
Portugal	5	5%
Seychelles	1	1%
Slovakia	1	1%
United Kingdom	2	2%
United States (USA)	60	60%

4.4.2 - Survey B – The impact of AI in intermodal transportation

Regarding this last survey, the sample includes 106 individuals. Concerning the respondent's gender distribution, 66 (62%) identified as masculine, 37 (35%) identified as female and 3 (3%) identified as other.

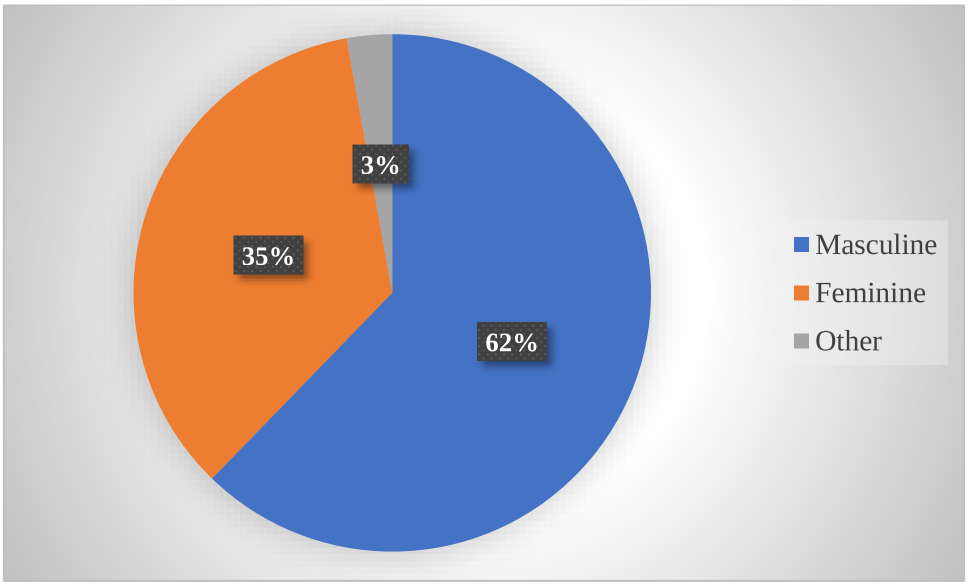

Figure 4.8 – Survey B's Gender Distribution

Regarding the age, 33 (34%) were between 18 and 25 years old, 49 (51%) were between 26 and 35 years old and 15 (corresponding to 15%) were between 36 and 50 years old.

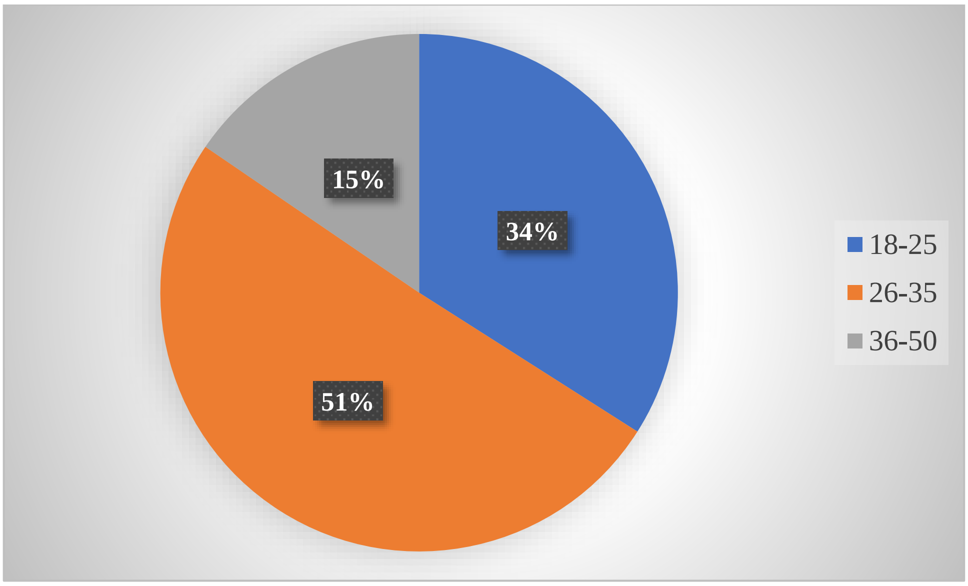

Figure 4.9 - Survey B's Age Distribution

Regarding the level of education obtained by the respondent's, 4 (4%) completed Elementary School, other 4 (4%) completed Intermediate school, 14 (13%) completed high school, 49 (47%) had an undergraduate degree, 27 (26%) a master's degree and 6 (6%) a PhD.

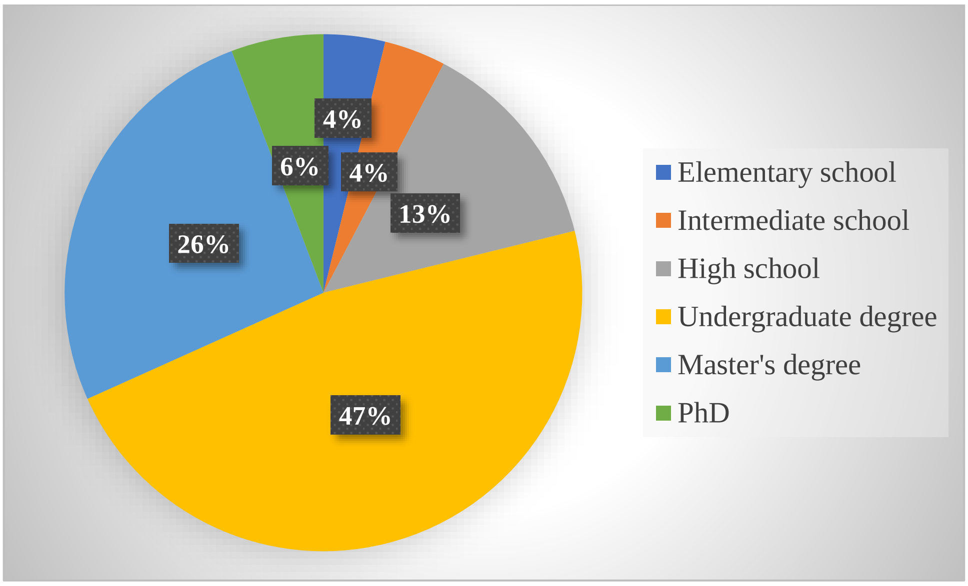

Figure 4.10 – Survey B's Level of Education

Regarding the years of experience in the area, 19 (18%) had less than 1 years' experience in the area, 17 (16%) had between 1 and 2 years' experience in the area, 37 (36%) had between 3 and 5 years' experience in the area, 15 (15%) had between 6 and 10 years and finally 16 (15%) respondents had more than ten years' experience in the area.

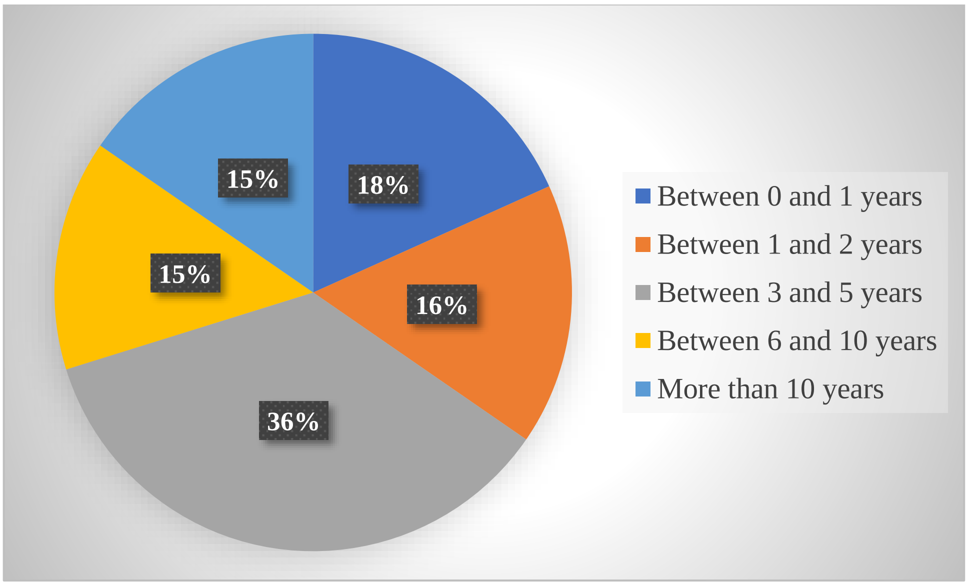

Figure 4.11 - Survey B's Years of Experience in the area

Regarding the nationality, the Table 4.4 – Survey B's respondents' Countries shows that 69 (66%) of the respondents were from the United States of America, 20 (20%) were from Portugal, 3 (3%) from Poland and 10 other countries had one respondent each.

Table 4.4 – Survey B's respondents' Countries

Country	**Number of Respondent's**	**% of Respondent's**
Armenia	1	1%
Aruba	1	1%
Australia	1	1%
Canada	1	1%
China	1	1%
Germany	1	1%
India	1	1%
Poland	3	3%
Portugal	20	20%
Serbia	1	1%
Singapore	1	1%
Slovakia	1	1%
United Kingdom	3	3%
United States (USA)	69	66%

Chapter 5 - Results Presentation and Discussion

5.1 - RQ1 - How do sociodemographic factors influence the knowledge about AI in the rail industry?

5.1.1 - Descriptive and Analytical Statistics Analyses

In order to do a sociodemographic analysis of the knowledge about AI in the rail industry, the first three questions of Survey A [Annex A], related to the knowledge about AI, ML and AI in the industry, respectively, were used in order to conduct a statistical analysis using, firstly descriptive statistics analysis and posteriorly by using analytical statistics to test and compare the sociodemographic differences. A simple descriptive analysis of these three questions is presented in Table 5.1, where the mean ($\bar{X}$), median, minimum and maximum values, standard deviation (s), kurtosis and skewness values are presented.

Table 5.1 – Descriptive statistics of the knowledge about AI survey questions

Descriptive statistics	Mean	Median	Min	Max	STDEV	Excess Kurtosis	Skewness
Knowledge about AI	4.311	4.000	2.000	5.000	0.851	2.441	-1.490
Knowledge about ML	4.139	4.000	1.000	5.000	0.944	1.184	-1.143
Knowledge about AI in the rail industry	3.557	4.000	1.000	5.000	1.142	-0.168	-0.720

After the analysis of the table above, is it possible to see that within the rail industry, the respondents are knowledgeable about Artificial Intelligence and Machine Learning, where, for both questions the mean is superior to 4, the median equal to that value and the distribution is leptokurtic. Regarding the third question, although over half of the respondents seem to be knowledgeable about the topic through the analysis of the median, the mean value is inferior to 4, showing that the respondents are less knowledgeable with the topic compared to the first two questions and the distribution is closer to being normal.

To analyze the internal differences related to these questions three socio-demographic factors were chosen from the survey, *Years of experience in the rail industry*, *Age* and *Level of Education*, and, after assuring the assumptions of the ANOVA, namely of the normality (through a visual check of the Q-Q plots and a confirmation with the Kolmogorov-Smirnov test), independence of the data (can be assumed due to the nature of the survey) and homogeneity of variances (through both a visual check using a Residuals vs Fit plot and the Levene's test), from the analysis of the ANOVA tests in Table 5.2, five proved not to be statistically significant.

Table 5.2 – ANOVA tests of the Knowledge of AI in the rail industry

ANOVA Tests	Groups	Sum of Squares	Degrees of Freedom	Mean Square	F value	p-value
AI Knowledge ~ Age	Between	2	13.26	6.629	13.96	**$4.61*10^{-6}$**
	Within	98	46.52	0.475		
AI Knowledge ~ Education	Between	5	7.09	1.4183	2.557	**0.0324**
	Within	95	52.69	0.5546		
AI Knowledge ~ Years	Between	5	4.97	0.9934	1.722	0.1370
	Within	95	54.82	0.5770		
ML Knowledge ~ Age	Between	2	6.71	3.357	2.373	0.0986
	Within	98	138.65	1.415		
ML Knowledge ~ Education	Between	5	4.17	0.8331	0.561	0.7301
	Within	95	141.20	1.4863		
ML Knowledge ~ Years	Between	5	8.58	1.716	1.557	0.18
	Within	95	104.67	1.102		
AI in Rail Knowledge ~ Age	Between	2	29.74	14.872	22.44	**$9.47*10^{-9}$**
	Within	98	64.95	0.663		
AI in Rail Knowledge ~ Education	Between	5	6.74	1.3477	1.456	0.2120
	Within	95	87.95	0.9258		
AI in Rail Knowledge ~ Years	Between	5	20.27	4.055	5.176	**0.0003**
	Within	95	74.42	0.783		

As can be confirmed through the analysis of the table above, starting from the first question, statistically significant differences (with a p-value inferior to 0.05) were present in the age and level of education sociodemographic factors and in the last question, related to the age of the respondents and their years of experience. In order to explore and compare these differences in each statistically significant sociodemographic factor, the Tukey's HSD test, a post-hoc ANOVA test was conducted.

5.1.2 - Comparison analysis of the knowledge about AI

Starting with the first question related to the respondent's knowledge about Artificial Intelligence, the two significant tests that were confirmed through the ANOVA tests were related to the age of the respondents and their level of education. Table 5.3 and Table 5.4 show the Tukey's HSD pairwise tests for these two factors with the lower and upper confidence interval values, the difference of the means between each of the group sample being tested and the adjusted p-value.

Table 5.3 – Tukey's test for the differences among age and knowledge about AI

Knowledge about AI ~ Age	Difference	Lower CI	Upper CI	*p-value* adjusted
26-35 ~ 18-25	-0.1403846	-0.5093834	0.2286142	0.6381966
36-50 ~ 18-25	-0.9340909	-1.3693303	-0.4988515	**0.0000048**
36-50 ~ 26-35	-0.7937063	-1.2309212	-0.3564914	**0.0001101**

Table 5.4 – Tukey's test for the differences in the level of education and knowledge about AI

Knowledge about AI ~ Education	Difference	Lower CI	Upper CI	*p-value* adjusted
HS ~ Elementary	-1.000000	-3.283415881	1.2834159	0.7984410
Intermediate ~ Elementary	0.0000000	-2.653089504	2.6530895	1.0000000
Master's ~ Elementary	-1.142857	-3.360072944	1.0743587	0.6655574
PhD ~ Elementary	-1.000000	-4.063523878	2.0635239	0.9323484
Undergraduate ~ Elementary	-0.5970149	-2.779359518	1.5853297	0.9676078
Intermediate ~ HS	1.000000	-0.693426540	2.6934265	0.5237316
Master's ~ HS	-1.428571	-1.005907223	0.7201929	0.9967065
PhD ~ HS	0.000000	-2.283415881	2.2834159	1.0000000
Undergraduate ~ HS	0.4029851	-0.366064634	1.1720348	0.6496869
Master's ~ Intermediate	-1.142857	-2.745901519	0.4601872	0.3098887
PhD ~ Intermediate	-1.000000	-3.653089504	1.6530895	0.8816979
Undergraduate ~ Intermediate	-5.970149	-2.151470870	0.9574410	0.8731518
PhD ~ Master's	0.1428571	-2.074358658	2.3600729	0.9999670
Undergraduate ~ Master's	0.5458422	0.004090173	1.0875943	**0.0471846**
Undergraduate ~ PhD	0.4029851	-1.779359518	2.5853297	0.9944910

Regarding the differences between the age ranges of the respondent's and their knowledge about Artificial Intelligence, statistically significant differences were present in the age ranges between 36 to 50 years old and 18 to 25 years old and 36 to 50 and 26 to 35 years old. The test conducted for the differences between the levels of education and their knowledge about AI revealed a statistically significant difference among the respondents with an undergraduate degree and a master's degree. The proximity of the p-value to one in these tests is explained by the value of the difference of the means being 0 due to the small N of some of the sociodemographic factors in-group samples and is better explained in the results section.

5.1.3 - Comparison analysis of the knowledge about AI in the rail industry

Starting with the final question related to the respondent's knowledge about Artificial Intelligence in the rail industry, the two significant tests that were confirmed through the ANOVA tests were related to the age of the respondents and their years of experience in the industry. Table 5.3 and Table 5.4 show the Tukey's HSD pairwise tests for these two factors with the lower and upper confidence interval values, the difference of the means and the adjusted p-value.

Table 5.5 - Tukey's test for the differences of age and knowledge about AI in the rail industry

Knowledge about AI in rail ~ Age	Difference	Lower CI	Upper CI	*p-value* adjusted
26-35 ~ 18-25	-0.1846154	-0.6206016	0.2513708	0.5737701
36-50 ~ 18-25	-1.3909091	-1.9051611	-0.8766571	**0.0020311**
36-50 ~ 26-35	-1.2062937	-1.7228798	-0.6897076	**0.0000007**

Table 5.6 - Tukey's test for the differences of years and knowledge about AI in the rail industry

Knowledge about AI in rail ~ Years of Experience	Difference	Lower CI	Upper CI	*p-value* adjusted
1-2 ~ 0-1	-0.26086957	-1.0989636	0.57722445	0.9442421
3-5 ~ 0-1	-0.84848485	-1.6327545	-0.06421517	**0.0260307**
6-10 ~ 0-1	-0.22222222	-1.2949094	0.85046499	0.9906158
>10 ~ 0-1	-1.31250000	-2.2227053	-0.40229472	**0.0008510**
3-5 ~ 1-2	-0.25000000	-1.6891609	1.18916091	0.9958635
6-10 ~ 1-2	-1.09027778	-2.1629650	-0.01759057	**0.0440600**
>10 ~ 1-2	-1.06250000	-2.5016609	0.37666091	0.2724345
6-10 ~ 3-5	0.01086957	-1.3838032	1.40554231	1.0000000
>10 ~ 3-5	-1.05163043	-1.8897244	-0.21353642	**0.0055802**
>10 ~ 6-10	-0.58761528	-1.2869055	0.11167496	0.1518447

Regarding the differences between the age ranges of the respondent's and their knowledge about Artificial Intelligence in the rail industry, statistically significant differences were present in the age ranges between 36 to 50 years old and 18 to 25 years old and 36 to 50 and 26 to 35 years old. The test conducted for the differences between the years of experience and their knowledge about AI in the rail industry revealed a statistically significant difference among the respondents with 3 to 5 and 0 and 1, over 10 and between 0 and 1, 6 to 10 and 1 to 2 and lastly over 10 and 3 to 5 years of experience in the industry. The proximity of the p-value to one in these tests is explained by the same limitation as the previous sub-chapter.

5.1.4 - Results Discussion

The first analysis conducted allows to assume based on descriptive statistics and the results from our survey that the respondents' level of knowledge about the topic of Artificial Intelligence and Machine Learning and the use of Artificial Intelligence in the rail industry, where a higher level of knowledge is present in AI and the uses of AI in the rail industry. In order to expand the analysis, three sociodemographic factors that constituted the last section of the survey in Annex A, age, years of experience in the rail industry and level of education were chosen to do this analysis. An analysis of variance (ANOVA) was performed with the assumptions checked beforehand for normality, homogeneity of variance and data independence.

Regarding the first question of the survey related to the level of knowledge in Artificial Intelligence, according to the results, it was the topic that the respondents were more knowledgeable about and where the answer's showed the least deviation ($\bar{X} = 4.311$; $s = 0.851$), which is in line with the literature where, according to Russell and Norvig (2021) and Haenlein and Kaplan (2019), although AI is a technology that is started being applied outside the academic world, people are quickly being accustomed to this technology. After the assumptions of ANOVA were confirmed, the ANOVA test's p-value was revealed to be statistically significant (p-value < 0.05) for the age and the level of education of the respondent's regarding their knowledge about AI, with their p-value being equal to $4.61*10^{-6}$ and 0.0324, respectively, indicating differences among those same factors regarding their knowledge about AI. To discover and understand these differences, the Tukey HSD's test was conducted to discover the statistically significant combinations and regarding the first factor of age, the p-value was significant for the age ranges between 36 to 50 years old and 18 to 25 years old and 36 to 50 and 26 to 35 years old and was significant regarding the level of education among respondents with an undergraduate degree and a master's degree. Regarding some values of the Tukey HSD's test, due to a small sample regarding the level of education the test presented some p-values closer to one, which can be attributed to the sample size of N=1 of respondent's that completed elementary school, intermediate school, and a PhD and is one of the limitations of this study. Nonetheless, the literature review backs these differences, as Haenlein and Kaplan (2019) and Horowitz & Kahn (2021) both mention these differences regarding the sociodemographic background of people and their knowledge about AI.

Regarding the second question of the survey about the knowledge of respondents regarding ML, unfortunately none of the ANOVA tests proved to be statistically significant, although according to the descriptive statistics analysis done, the respondents were still shown to be knowledgeable about the topic ($\bar{X} = 4.139$; $s = 0.944$), which once again confirms what Russell and Norvig (2021) mention about the topic of AI. One of the explanations that can be given for the lack of statistical differences of the knowledge about ML and that is backed by the authors is the fact that while the general concept of AI is broader and more used as a commercial term, it's subfields and more specific topics are still being understood as synonyms. In the conclusions and suggestions for future studies, some alternatives are suggested to conduct a deeper investigation about the topic.

Lastly, the third question, regarding the knowledge of respondents about the use of Artificial Intelligence in the rail industry, it was the topic that respondents showed the least knowledge of the three questions, where although more than half the respondents were shown to be knowledge about this topic, it was where the mean value was the lowest and more variation of the answers was showed ($\bar{X} = 3.557$; $s = 1.142$), where although the literature was more limited regarding the knowledge about AI in the industry, Horowitz & Kahn (2021) mention that the knowledge about AI in the different industries has been rising since the beginning of this century. After the assumptions of ANOVA were confirmed, the test's p-value was revealed to be statistically significant ($p\text{-value} < 0.05$) for the age and years of experience of the respondent's regarding their knowledge about AI, with their p-value being equal to $9.47*10^{-9}$ and 0.0003, respectively, indicating differences among those same factors regarding their knowledge about AI. To discover and understand these differences, the Tukey HSD's test was conducted to discover the statistically significant combinations and regarding the first factor of age, the p-value was significant for the age ranges between 36 to 50 years old and 18 to 25 years old and 36 to 50 and 26 to 35 years old and was significant regarding the professional experience among respondents with 3 to 5 and 0 and 1, over 10 and between 0 and 1, 6 to 10 and 1 to 2 and lastly over 10 and 3 to 5 years of experience in the industry. Nonetheless, the literature review once again backs these differences, as Horowitz & Kahn (2021) both mention these differences regarding the sociodemographic background and their knowledge related to the projects being implemented in the different industries.

5.2 - RQ2 – What is the possibility to implement AI in the rail industry?

5.2.1 - Statistical Analysis

Using the same five-point Likert scale (Likert, 1932) as the one used in the last research question, this next two research questions will use the SEM-PLS approach in order to analyze the collected data from both surveys and starts by assessing the measurement model and conduct the evaluation of the structural model. Regarding this second RQ of the study of the *possibility to implement AI in the rail industry* [Annex A], it was constituted of 22 questions for use in this RQ, each one related to one indicator.

To assess the measurement models, according to Hair et al. (2017), the first stage involves the evaluation of the reliability of the individual indicators' outer loadings, which all except two exceed 0.6 and that, according to the author, confirms the reliability of the individual indicators. This led to the removal of one indicator, related to the *Benefits of AI* variable, namely the 11 – Productivity rate. Following the removal of this indicators, to access the internal consistency reliability, the Cronbach's alpha and the CR values were confirmed to be above 0.7, so the internal consistency reliability was assured, as can be seen in Table 5.7.

Table 5.7 – SEM-PLS Measurement Model Evaluation for the first SEM-PLS Analysis

Latent Variables	Cronbach's Alpha	Composite Reliability	AVE	1	2	3	4
1) Benefits of AI	**0.954**	**0.961**	**0.710**	**0.843**	0.766	0.168	0.616
2) Impact of AI	**0.768**	**0.896**	**0.812**	0.658	**0.901**	0.365	0.842
3) Risks of AI	**0.808**	**0.837**	**0.594**	0.131	0.375	**0.628**	0.381
4) Trust in AI	**0.774**	**0.859**	**0.753**	0.775	0.746	0.263	**0.868**

Note: In the last four columns, the numbers that are black and bold in the diagonal represent the square roots of the AVE, below those represent the correlation between the constructs and above the diagonal the HTMT ratios.

Following the reliability assessment, the AVE values were all superior to 0.5 (Bagozzi & Yi, 1988), confirming the value needed for convergent validity according to the authors. To evaluate the discriminant validity, the first criteria is that the square root of each construct's AVE has to have a bigger value than its highest correlation with any other construct (Fornell &

Larcker, 1981). Secondly, according to the *Heterotrait-Monotrait* (HTMT) ratio (Henseler et al., 2015), all HTMT values should be below 0.85, according to the more conservative approach from the author, as is shown in the table.

In order to assess the SEM-PLS structural model, VIF values were to check the inexistence of collinearity, which, according to Hair et al. (2017) translates into a VIF value inferior to 5, which was true for the model. Additionally, the value of the coefficient of determination (R^2) for the endogenous variables of the model, *Trust in AI* and *Impact of AI* were equal to 62.8% and 61.3%, respectively, which is superior to the 10% threshold set by the authors to measure predictive accuracy and the Stone-Geisser's (Q^2) value was equal to 0.457 in relation to the *Trust in AI* variable and 0.482 for the *Impact of AI* variable, superior the value of 0 to confirm predicative relevance.

Table 5.8 – Direct Effects of the first SEM-PLS Analysis

Direct Effects	**Path Coefficients**	**Standard Deviation**	**T-Statistics**	***p-values***
Benefits of AI -> Impact of AI	0.239	0.112	2.125	**0.034**
Benefits of AI -> Trust in AI	0.754	0.049	15.292	**0.000**
Risks of AI -> Impact of AI	0.211	0.089	2.374	**0.018**
Trust in AI -> Impact of AI	0.505	0.106	4.754	**0.000**

Table 5.9 - Indirect Effects of the first SEM-PLS Analysis

Indirect Effects	**Path Coefficients**	**Standard Deviation**	**T-Statistics**	***p-values***
Benefits of AI -> Trust in AI -> Impact of AI	0.381	0.084	4.523	**0.000**
Risks of AI -> Trust in AI -> Impact of AI	0.083	0.058	1.436	**0.152**

To interpret the quantitative results, and by using the bootstrapping procedure results for the direct effects as shown in Table 5.8, the *Benefits of AI* has a significant positive effect on the trust in AI and its intention to be integrated in the rail industry, confirmed by its Path Coefficient (β) and the p-value (β = 0.754; p = 0.000 and β = 0.239; p = 0.034). The hypotheses related to this variable (H1a and H1b) are also confirmed, and for the same reasons, the variables *Risks of AI* and *Trust in AI* also produced a significant effect on the intention to integrate AI in the rail industry (β = 0.211; p = 0.018 and β = 0.505; p = 0.000), confirming hypothesis H2 and H3a.

Regarding the mediating hypotheses (H3b and H3c), and using the bootstrapping procedure already mentioned (Hair et al., 2017), the indirect effects of the *Benefits of AI* through the mediator of *Trust in AI* on the *Impact of AI* and of the *Risks of AI* through the *Trust in AI* on the *Impact of AI* are shown in Table 5.9, where the hypothesis related to this effects are confirmed as the p-values are statistically significant, with p-value <0.05 (β = 0.381; p = 0.000 and β = 0.083; p = 0.152, respectively).

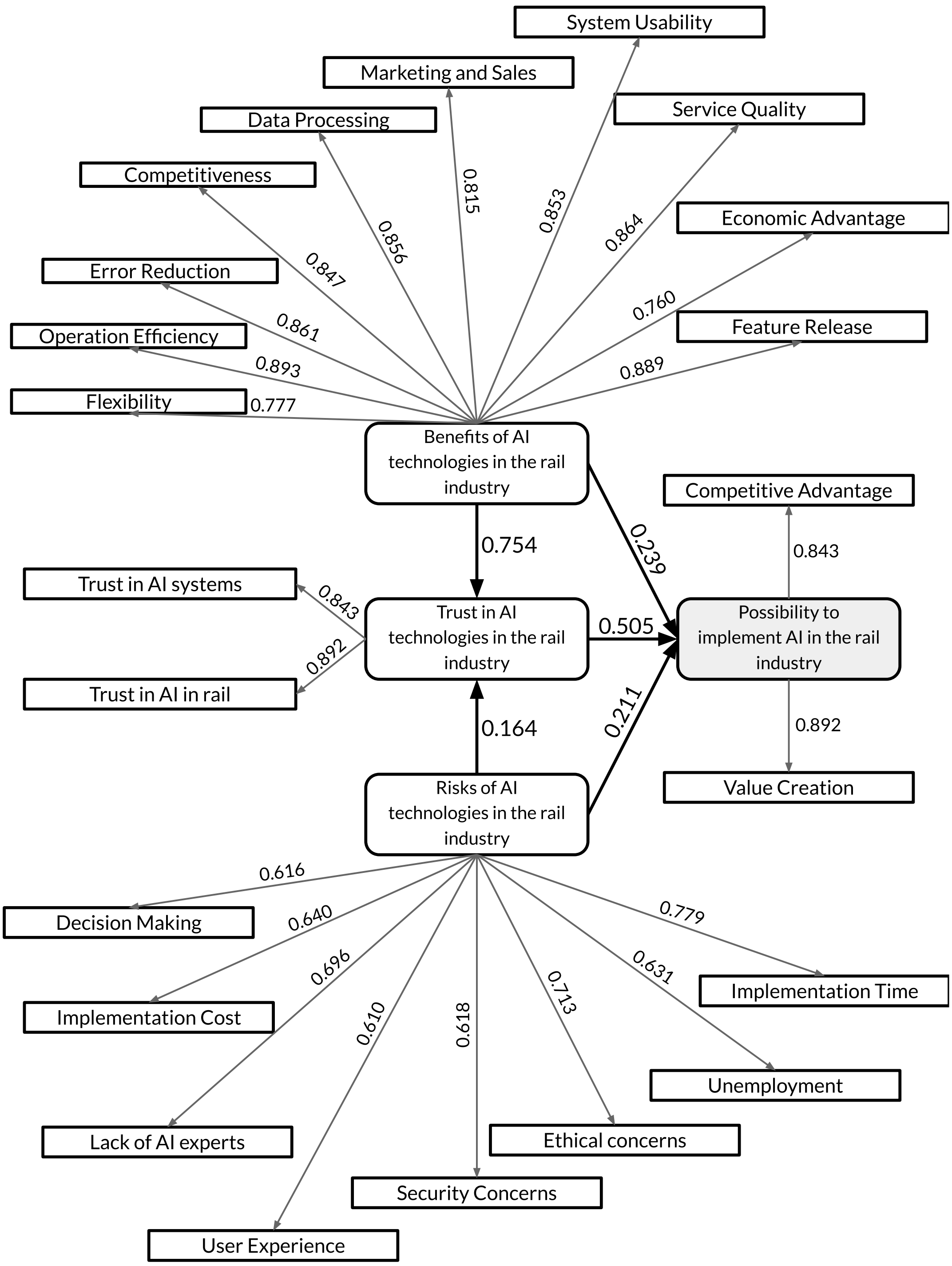

Figure 5.1 – RQ2’s Conceptual Model results

5.2.2 - Results Discussion

With the help of the software *SmartPLS 3*, the tests conducted above intended to answer the second Research Questions that is related to this objective of the study of the possibility to implement Artificial Intelligence in the rail industry. This RQ was related to the three main factors being analyzed in this section, of the *Benefits of AI, Risks of AI* and *Trust in AI* in the rail industry. Each of the variables being analyzed used several indicators based in the literature review previously conducted.

In the case of the *Benefits of AI*, the indicators were *Economical competitive advantage* (Martínez-López and Casillas, 2013; Costa, 2020), *Environmental Adaptation* (Russell and Norvig, 2021), *Data processing efficiency* (Gil et al., 2021), *Error reduction* (Lim et al., 2020), *User adaptability* (Yang et al., 2020), *Feature innovation* (Qu et al., 2021), *System Quality* (Lee et al., 2021) and *Operations and processes efficiency* (Gupta et al., 2021). Due to not contributing to the model, the indicator *Productivity gains* (Damioli et al., 2021) was removed. The decision to add this variable to the model was based on the benefits mentioned in the literature that this technology can bring to the different areas of the rail industry. Regarding the risks, the indicators were related to *Cost Implementation* (Jordan, 2020), *Biased decision making* (Russell and Norvig, 2021, *Implementation time* (Shaw et al., 2019), *HCI issues* (Russell and Norvig, 2021) and *Shortage of AI experts* (Russell and Norvig, 2021), *Impact on employment* (Harari, 2015; Yang, 2020) and *Ethical doubts* (Berente et al., 2021) what as can been seen, were all based on the literature, that showed that these risks have been delaying the implementation of AI in the industry. One limitation found in the literature is that recent implementation failures of projects including AI technologies in the rail industry due to the COVID-19 pandemic have distorted the trust in this technology and therefore the influence of risks of AI in its trust in the industry was not considered and a suggestion is made in the conclusions chapter to conduct an investigation in the future.

Finally, regarding the analysis of the last hypothesis related to the variable *Trust in AI*, the indicator *Trust in AI rail systems* (Wonglakorn et al., 2021) was used. The decision to use this variable in our model is that, according to the literature, the trust in AI has been increasing because of the benefits it has been shown in projects already implemented and has led companies to implement AI in the industry. According to the authors, the trust in new technologies, such as Artificial Intelligence is a key factor in the will to implement this type of systems. Regarding the variable *Impact of AI*, an additional indicator was added of the *Interest in implementing AI in the rail industry* and was used in order to assess the model.

Regarding the hypothesis being tested, as previously mentioned, all of the direct effects presented in our model were supported by the results presented. Firstly, regarding the hypotheses related to the influence of AI on the trust in AI and the will to implement it, both were found to be statistically significant ($p = 0.000$ and $p = 0.034$, respectively) and Hypotheses H1a and H1b were accepted, confirming the literature previously conducted where it was shown that companies were implementing AI based on the benefits that it brought and those benefits were in turn increasing the trust in the technology (Damioli et al., 2021; Qu et al., 2021).

The hypothesis related to the variable related to the *Risks of AI*, namely that those risks present an effect for the implementation of AI in the rail industry, was also confirmed, with the p-value equal to 0.018, inferior to the significant value of 0.05. The results related to the acceptance of this Hypothesis H2 were once again in line with the literature presented that companies implement AI systems without regarding the risks associated (Jordan, 2020; Yang, 2020; Shaw et al., 2019). The third direct effect that was tested in the model was related to the hypothesis that *The trust of AI impact positively in the possibility to implement AI in the rail industry*. The hypothesis H3a was accepted as, once again, the p-value was equal to 0.007, inferior to the statistically significant value of 0.05 and confirms that the trust this technology has seen since it's been implemented in the industry has influenced the will to implement these projects (Wonglakorn et al., 2021).

Two mediation hypotheses were present in this model, those being the mediator effect between of the *Trust in AI* between the *Risks* and *Benefits of AI* and the possibility to *Implement AI*, corresponding to hypotheses H3b and H3c respectively, were accepted in our model ($p= 0.000$ and $p = 0.152$), that according to the literature, can be attributed to the projects of AI in the industry that have been implemented and shown that the benefits and the risks will influence the trust in the technology and will consequently lead to an increased possibility to implement these kinds of projects (Shaw et al., 2019; Jordan, 2020; Wonglakorn et al., 2021).

5.3 - RQ3 – What is the possibility to implement AI in the intermodal transportation?

5.3.1 - Statistical Analysis

Using the same five-point Likert scale (Likert, 1932) as the one used in the last two analysis, this next research question will use the SEM-PLS approach in order to analyze the collected data from both surveys and starts by assessing the measurement model and conduct the evaluation of the structural model. Regarding this second RQ of the study of the *impact of AI* *in intermodal transportation* [Annex B], it was constituted of 24 questions for use in this objective, each one related to one indicator.

In order to access the results of the measurement models, as can be seen in Table 5.10 (see note for Table 5.9), according to Hair et al. (2017), the evaluation of the reliability of the individual indicators' outer loadings, which all exceeded 0.6 which, according to the author, confirms the reliability of the individual indicators. Regarding the assessment of the model's internal consistency reliability, all the Cronbach's alpha and the CR values were all found to be above 0.7, except for the variables *Impact of AI* and *Trust in AI* which, according to the author, the true internal consistency is between the Cronbach's alpha and the CR, so the consistency was assured.

Table 5.10 - SEM-PLS Measurement Model Evaluation for the second SEM-PLS Analysis

Latent Variables	Cronbach's Alpha	Composite Reliability	AVE	1	2	3	4	5
1) Awareness of AI	**0.700**	**0.814**	**0.522**	**0.723**	0.736	0.375	0.579	0.744
2) Benefits of AI	**0.878**	**0.902**	**0.508**	0.594	**0.713**	0.717	0.508	0.698
3) Impact of AI	**0.623**	**0.841**	**0.726**	0.248	0.530	**0.852**	0.545	0.690
4) Risks of AI	**0.707**	**0.782**	**0.547**	0.403	0.386	0.391	**0.740**	0.402
5) Trust in AI	**0.673**	**0.857**	**0.750**	0.503	0.550	0.455	0.286	**0.866**

Following the reliability assessment, the AVE values were all superior to 0.5 (Bagozzi & Yi, 1988), confirming the value needed for convergent validity according to the authors. To evaluate the discriminant validity, the first criteria is based on the fact that the square root of each construct's AVE has to have a bigger value than its highest correlation with any other construct (Fornell & Larcker, 1981). Secondly, according to the *Heterotrait-Monotrait* (HTMT) ratio (Henseler et al., 2015), all HTMT values should be below 0.85, according to the more conservative approach from the author, as is shown in the table.

In order to assess the SEM-PLS structural model, VIF values were to check the inexistence of collinearity, which, according to Hair et al. (2017) translates into a VIF value inferior to 5, which was true for the model. Additionally, the value of the coefficient of determination (R^2) for the endogenous variables of the model, *Awareness of AI, Trust in AI* and *Impact of AI* was equal to 33.8%, 30.9% and 38.7% respectively, superior to the 10% threshold set by the authors to measure predictive accuracy and the Stone-Geisser's (Q^2) values were equal to 0.184, 0.218 and 0.248 for the same three variables, superior the value of 0 to confirm predicative relevance.

Table 5.11 - Direct Effects of the second SEM-PLS Analysis

Direct Effects	Path Coefficients	Standard Deviation	T-Statistics	*p-values*
Awareness of AI -> Impact of AI	0.243	0.118	2.064	**0.040**
Benefits of AI -> Awareness of AI	0.515	0.083	6.201	**0.000**
Benefits of AI -> Impact of AI	0.432	0.123	3.500	**0.001**
Benefits of AI -> Trust in AI	0.517	0.072	7.211	**0.000**
Risks of AI -> Impact of AI	0.246	0.084	2.910	**0.004**
Risks of AI -> Trust in AI	0.086	0.108	0.795	**0.427**
Trust in AI -> Impact of AI	0.269	0.100	2.696	**0.007**

Table 5.12 - Indirect Effects of the second SEM-PLS Analysis

Indirect Effects	Path Coefficients	Standard Deviation	T-Statistics	*p-values*
Risks of AI -> Awareness of AI -> Impact of AI	-0.050	0.036	1.394	**0.164**
Benefits of AI -> Awareness of AI -> Impact of AI	-0.125	0.071	1.753	**0.080**
Benefits of AI -> Trust in AI -> Impact of AI	0.139	0.052	2.694	**0.007**

To interpret the quantitative results, and by using the bootstrapping procedure results for the direct effects as shown in Table 5.8, the *Benefits of AI* have a significant positive effect on the *Awareness of AI*, *Trust in AI* and its intention to be integrated in the rail industry, confirmed by its Path Coefficient (β) and the p-value (β = 0.0.515; p = 0.000 , β = 0.517; p = 0.000 and β = 0.515; p = 0.000). The hypotheses related to this variable (H1a, H1b and H1c) are also confirmed, and for the same reasons, the variables *Risks of AI* and *Trust in AI* also produced a significant effect on the intention to integrate AI in the rail industry (β = 0.211; p = 0.018 and β = 0.505; p = 0.000), confirming hypothesis H2a and H3a. Regarding the *Awareness in AI*, the variable has a significant effect on the *Impact of AI* (β = 0.040; p = 0.018), thus confirming hypothesis H4a. The influence of the *Risks of AI* on the *Trust in AI* was not confirmed through the analysis of the model, as the p-value was not statistically significant (β = 0.269; p = 0.007) and consequently rejecting hypothesis H2b.

Regarding the mediating hypotheses (H3b and H4b), and using the bootstrapping procedure already mentioned (Hair et al., 2017), the indirect effects of the *Benefits of AI* through the mediator of *Trust in AI* on the *Impact of AI* and of the *Benefits of AI* through the *Awareness in AI* on the *Impact of AI* are shown in Table 5.9, where the first hypothesis (H3b) related to this effect is accepted (β = 0.139; p = 0.007) and the second hypothesis (H4b) is rejected (β = -

0.125; p = 0.080). The indirect effect of the *Risks of AI* on the mediator variable of the *Awareness of AI* on the *Impact of AI* also presents a non-significant p-value (β = -0.050; p = 0.164), thus rejecting hypothesis H4c.

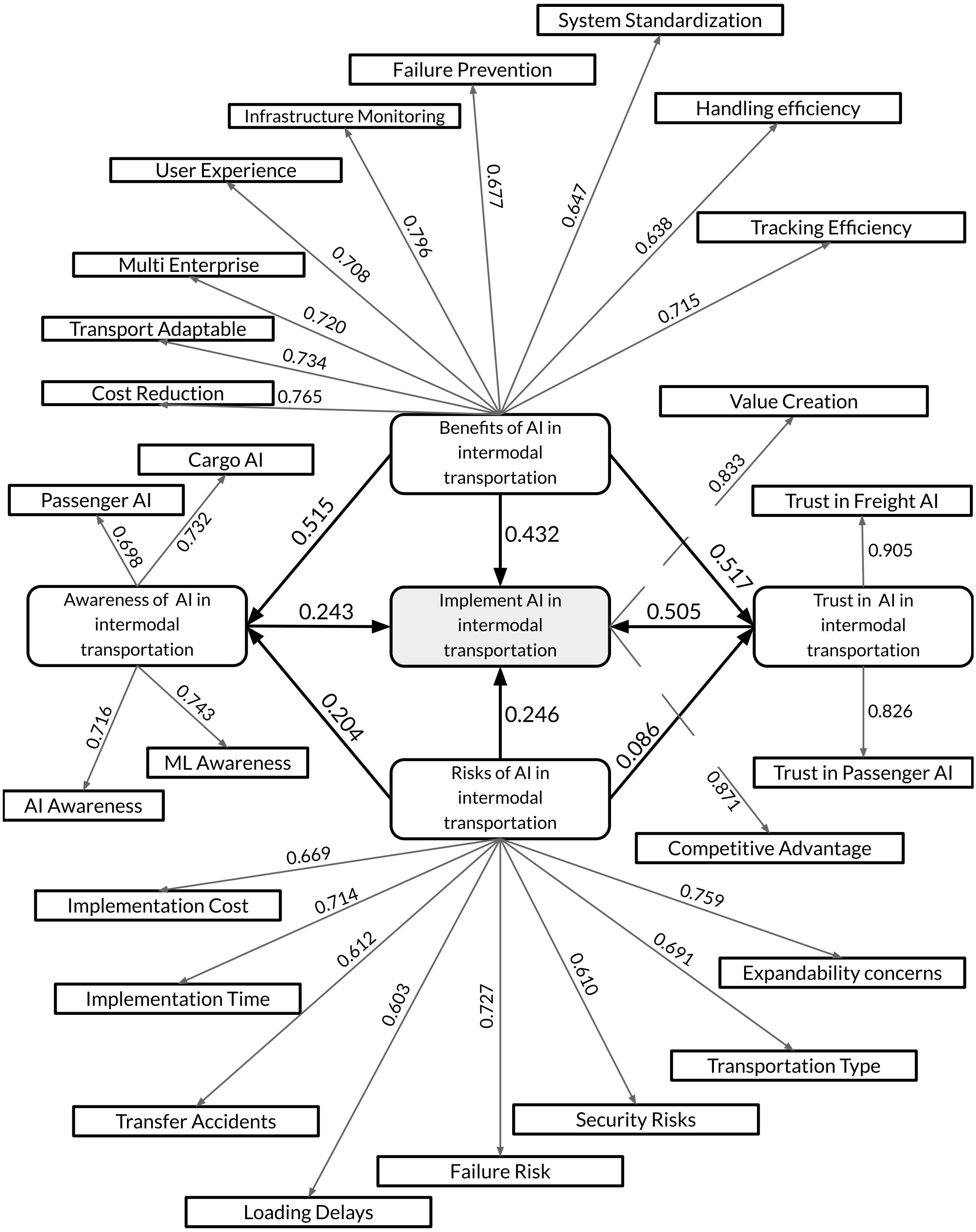

Figure 5.2 – RQ3's Conceptual Model results

5.3.2 - Results Discussion

The analysis regarding this RQ was similar to the one conducted in the section before and is related to four different hypotheses. Each of the variables being analyzed used several indicators, also based in the literature review. In the case of the *Benefits of AI*, the indicators were *Cost Savings* (Singh et al., 2021), *Flexibility* (Singh et al., 2021), *Better user experience* (de Abreu e Silva & Bazrafshan, 2013), *Monitoring efficiency* (Balster et al., 2020), *Failure Adaptability* (Bahtizin et al., 2019), *System Standardization* (EU, 2019), and *Tracking efficiency* (Pfoser et al., 2016). The previous literature review confirms the benefits that AI can bring to intermodal transportation and therefore, this variable was added to the model. Regarding the risks, the indicators that influenced the hypothesis acceptance were the *Implementation Cost* (Givoni & Banister, 2006; Wang et al., 2017), *Implementation Time* (Ishfaq & Sox, 2012), *Cargo Loss* (Filina-Dawidowicz et al., 2020; Hintjens et al., 2020; Lorenc & Kuźnar, 2021), *Transfer Accidents* (Janic, 2007), *Loading/Unloading Delays* (Zhang & Li, 2020), *System failure* (Dong et al., 2018; Hosseini & Barker, 2016), *Security concerns* (Nair et al., 2010) and *Expandability concerns* (Iannone, 2012) . The decision to add this variable to the model was based on the risks mentioned in the literature that this technology can bring to the implementation of AI in intermodal terminals.

Regarding the analysis of the hypothesis related to the variable *Trust in AI*, the indicators Trust in AI freight intermodal transportation (Rusca et al., 2019) and Trust in AI passenger intermodal transportation (Wonglakorn et al., 2021) were used. Although the authors base their research on different aspects of the intermodal transportation, all affirm that the trust in Artificial Intelligence can impact both the passenger and freight cargo. Differently to the variables present in the last model, the *Awareness of AI* with the indicator *Awareness of AI technologies* (Horowitz & Kahn, 2021; Gambardella et al., 1998) is added as the implementation of this kinds of projects have only started very recently according to the literature. Regarding the variable *Impact of AI*, an additional indicator was added of the *Interest in implementing AI in intermodal transportation* and was used in order to assess the model.

Regarding the hypothesis being tested related to the direct effects of the model, all with the exception of hypothesis H2b were accepted. Firstly, regarding the *Benefits of AI* variable, the influence of the variable on the *Awareness of AI, Trust in AI* and *Impact of AI* was all found to be statistically significant, with $p<0.05$, and therefore confirming hypotheses H1a, H1b and H1c, confirming the literature that was previously conducted where it was shown that companies were implementing AI based on the benefits that it brought and those benefits were in turn increasing the trust and awareness in the technology (Bahtizin et al., 2019; EU, 2019; Singh et al., 2021).

The hypothesis related to the variable related to the *Risks of AI*, namely that those risks present an effect for the implementation of AI in the rail industry, was also confirmed, with the p-value equal to 0.004, inferior to the significant value of 0.05. The results related to the acceptance of this Hypothesis H2a was once again in line with the literature presented relating that companies will implement AI regardless of the risks of the technology. Regarding the influence of the *Risks of AI* on the *Trust in AI* the hypothesis was not accepted as the p-value was not statistically significant (p-value = 0.427). This can be explained due to the current COVID-19 pandemic, where the literature indicates that the risks of AI have been over perceived temporarily and negatively impacted the trust of the industry in the technology (Filina-Dawidowicz et al., 2020; Hintjens et al., 2020). Nonetheless, and differently from last analysis, this effect was kept as no direct literature related to intermodal transportation was found. The third variable's direct effects that was tested in the model was related to hypothesis that *The trust of AI impact positively in the possibility to implement AI in the rail industry*. The hypothesis H3a was accepted as, once again, the p-value was equal to 0.007, inferior to the statistically significant value of 0.05 and confirms that the trust this technology has seen since it's been implemented in the industry has influenced the will to implement these projects (Rusca et al., 2019; Wonglakorn et al., 2021). Regarding the hypotheses related to the variable *Awareness of AI,* its influence on the *Impact of AI* was statistically significant and there the hypothesis H4a was accepted, what is in line with the literature that the trust in the technology influences how companies perceive a possible implementation of this technology in their systems (Horowitz & Kahn, 2021).

Three mediation hypotheses were present in this model, the first being the mediator effect between of the *Trust in AI* between the *Benefits in AI* and the possibility to *Implement AI,* corresponding to hypothesis H3b, which was accepted in our model (p= 0.007) and that, according to the literature, can be attributed to the projects of AI in the industry that have been implemented and shown that the benefits will influence the trust in the technology and will consequently lead to an increased possibility to implement these kinds of projects (EU, 2019; Rusca et al., 2019; Wonglakorn et al., 2021). The two other hypotheses related to the indirect effects were rejected (p-values equal to 0.164 and 0.080, respectively), those being the mediator effect between of the *Awareness in AI* between the *Benefits and Risks in AI* and the possibility to *Implement AI,* corresponding to hypotheses H4b and H4c, where, according to the literature, can be attributed to the present relevance of the technology not affecting how the industry plans to implement the technology (Filina-Dawidowicz et al., 2020; Horowitz & Kahn, 2021).

5.4 - Integrated Results Discussion

As previously mentioned, the individual data discussion that was done previously only allows to explain partially the relation between each of the research questions being analyzed. Additionally, Figure 5.3 illustrates not only the relation but also the specificity of the topics being researched, namely between the Knowledge about Artificial Intelligence and its sociodemographic analysis, the impact of AI in the rail industry and its impact on intermodal transportation.

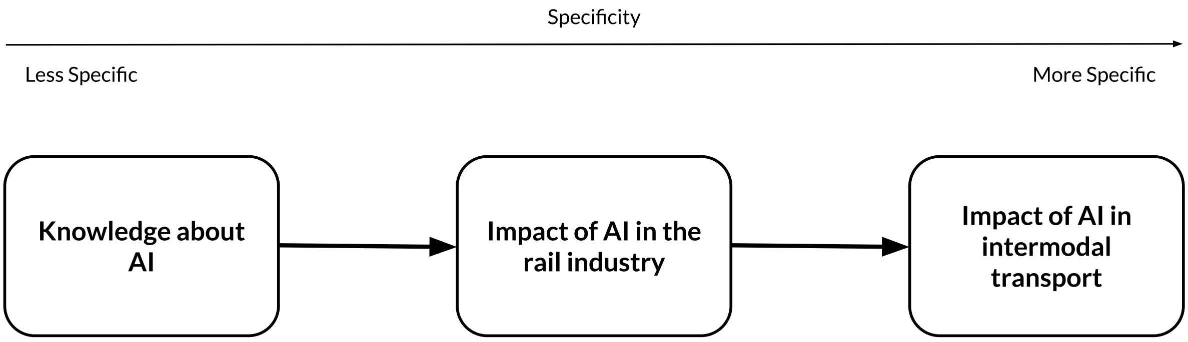

Figure 5.3 – Specificity of the thesis data analysis

Starting from the sociodemographic analysis of the Knowledge about Artificial Intelligence, the results supported the literature review where Russell and Norvig (2021) and Haenlein and Kaplan (2019) mention that the knowledge of Artificial Intelligence in the rail industry is increasing. The authors mention that knowledge in this technology can contribute to the implementation of AI in the different industry systems. Additionally, differences were present between the different age ranges and level of education and their knowledge about AI and between the age ranges and years of experience and the knowledge about the implementation of AI projects.

The objective of studying the possibility to implement Artificial Intelligence in the rail industry was complemented by the analysis of the knowledge already mentioned, and by the confirmation of the hypothesis formulated about the benefits, risks and trust in Artificial Intelligence. This confirmation of the hypothesis once again confirmed the literary review they were based on, as authors such as Givone and Zhang et al. (2018) and Yin et al. (2020) state that the implementation of disruptive technologies such as Artificial Intelligence can allow companies to increase their competitive advantage in comparison to other rail companies.

The second objective of the thesis of the study of Artificial Intelligence in intermodal transportation not only shows the increased specificity of the topics being analyzed but additionally of the confirmation of the majority of the hypotheses related to the influence of the trust, risks, awareness and benefits influence the implementation of these systems. Although intermodal transportation encapsulates multiple types of transport, both passenger and cargo, and includes the railway, the literature supports the results with authors such as Nair et al. (2010) and Ishdaq and Sox (2012) stating that the impact that new technologies can bring to the implementation in intermodal transport systems and Filina et al. (2020) mentioning the impact of Artificial Intelligence.

To conclude, and according to our literature and our results, when analyzing the two objectives, not only their relation can be discussed, but also how the differences in their specificity may affect the analysis of the results, as from less specific to more specific, the literary review already mentioned confirms the relation between the knowledge in Artificial Intelligence, the impact of Artificial Intelligence in the rail industry and its impact on intermodal transport systems.

Conclusion

Final Considerations

The appearance of disruptive technologies affected how the different companies and industries operated and the implementation of Artificial Intelligence can present as an alternative to traditional methods to gain a competitive advantage (Costa et al., 2020 and Damioli et al., 2021). This thesis pretended to study the impact of Artificial Intelligence in the rail industry through two objectives, the possibility to implement AI in the rail industry and to implement it on intermodal transport systems and studied the impact of factors such as the benefits, risks, knowledge and trust do this investigation.

The first step involved an extensive literature review, which was constituted of two parts, the first one involving Artificial Intelligence technologies, algorithms and techniques, where it’s definition, history, subfields and real-world applications were all interconnected with the literature review of the rail industry and intermodal terminals and the different implementations of Artificial Intelligence in its systems. The second step of the collection of the necessary data and its respective analysis was done using two surveys with over 100 answers each and allowed to reach conclusions related to the impact of the knowledge, benefits, risks and trust of Artificial Intelligence in the rail industry and intermodal transportation.

Regarding the first survey of the analysis of the impact of AI in the rail industry, two different analyses were made using different tools, where the first related the sociodemographic differences and a descriptive statistical analysis of the knowledge of Artificial Intelligence in the rail industry. According to our results, while there is a statistical confirmation through descriptive statistics that the respondents had a high knowledge about AI technologies, the knowledge about the implementation of AI in the rail industry, using the Likert scale, presented lower overall results of the knowledge and greater discrepancies of the responses among the respondents.

To further analyze the two topics, following the brief descriptive statistics analysis, and to try to confirm the literature review of the differences in the sociodemographic factors among new and disruptive technologies (Russell and Norvig, 2021 and Haenlein and Kaplan, 2019), analyses of variance tests were conducted, where the results showed how the internal differences among the different age ranges and level of education among the respondents influenced their knowledge about Artificial Intelligence, which is also in line with the literature presented for this research question. An additional two sociodemographic factors of the age and years of experience in the rail industry also showed internal differences related to the knowledge of Artificial Intelligence and its implementation in the rail industry, which although the literature review related to the knowledge of AI related to the rail industry was limited, Russell and Norvig (2021) state that the experience of a worker can produce an effect on the implementation of disruptive projects, especially with an high Research and Development (R&D) time of implementation.

Using the same survey as the one used for the statistical analysis using the analysis of variance, the first objective's analysis was concluded through the use of the SEM-PLS approach to evaluate the impact of the benefits, risks and trust of Artificial Intelligence in the rail industry. Moreover, and doing a more detailed analysis of the results, the first hypothesis related to this part of the analysis of *the benefits of implementing AI technologies in the rail industry* and, proved that the different benefits that the disruptive technology that Artificial Intelligence influences its implementation in the rail industry. The same can be said for the hypothesis being analyzed of *the trust in the implementation of AI in the rail industry* that also showed how it influenced the implementation of this kind of systems. Lastly, the hypothesis of *the risks of implementing AI technologies in the rail industry* and the hypothesis related that companies would implement AI in rail regardless of the risks, what, not only for this hypothesis, but for this three being discussed, can be answered not only with the acceptance of the hypothesis but from the contributions from the literature.

To do the analysis and reach the conclusions related to the second objective of the thesis of *the impact of AI in intermodal transportation?*, the second survey answers allowed to once again use the SEM-PLS approach in order to evaluate the impact of the benefits, risks, trust and awareness of Artificial Intelligence in intermodal transportation and, continue our analysis towards a more specific topic of discussion. In this objective, the literature review proved to be once again concordant with the results and their influence was shown from these different factors. With the exception of the hypothesis relating the effects of the risks of this technology on its awareness, every other hypothesis was accepted due to its statistical significance.

More specifically, when analyzing the relation between the four hypothesis and the third research question, the first hypothesis of *What are the benefits of implementing AI technologies in intermodal transportation?*, the benefits of AI proved to influence these kinds of systems, conforming with the existing literature mentioned in the analysis. The second hypothesis that could influence in the implementation of this systems was of *What are the risks of implementing AI technologies in intermodal transportation?* and was confirmed with both the acceptance of the hypothesis and the literary review. Regarding the third hypothesis that was formulated based on the influence the risks of this technology, of *What is the awareness of AI technologies in intermodal transportation?*, the hypothesis was confirmed once again with the literature and the confirmation of the hypothesis. The fourth and final hypothesis is related to the trust of Artificial Intelligence in intermodal transportation, namely *What is the trust in the implementation of AI in intermodal transportation?* and was in line with the literature and confirmed through the hypotheses formulated.

To conclude, this thesis allowed to show the impact of different factors related to Artificial Intelligence in the rail industry and in intermodal transportation and, in order to do this, an extensive literature review was conducted including topics related to Artificial Intelligence and the rail industry. To confirm the literature review, then hypotheses were formulated related to the research questions and two surveys were conducted and a statistical analysis was conducted in order to accept those hypotheses. The last step involved the discussion and conclusion of the data and was divided into individual discussion related to each one of the analyses and a final discussion, that related all the analysis with the two objectives.

Contribution for the state of the art

The implementation of Artificial Intelligence in the rail industry and intermodal systems has only started to be deployed in the last ten years and, while the literature related to the topics and concepts of Artificial Intelligence and its related concepts, the rail industry, and of intermodal systems, is vast, the impact that such the implementation of such a disruptive technology can bring in these two industries is limited. Regarding the first objective of the impact of AI in the rail industry, the analysis conducted on the sociodemographic differences of the knowledge about this technology allowed to confirm much of the literature present related to the knowledge of Artificial Intelligence, and to complement the literature related to the rail industry.

The analysis of the benefits, risks and trust and its influence on the rail industry allowed to confirm what was said mentioned by authors such as Šotek et al. (2021) or Pyrgidis (2016) related to the different factors that influence the implementation of these systems in the industry. Regarding the second objective, the literature proved to be more limited and while an exploratory type of research was conducted in the preliminary stages of the literature review, this investigation pretends to complement and contribute to the literature related to this industry.

Contribution to the rail industry

The rail industry is connected with industries such as Logistics where the implementation of system being integrated with Artificial Intelligence are still limited and new and where the systems already in use differ vastly from each other. Additionally, the vast and different areas that the industry works with presents another challenge to the implementation of these kind of systems. This thesis pretended to enrich the knowledge about AI systems in the rail industry by studying it's possible positive and negative factors that could affect its implementation.

Moreover, the conclusions and discussion related to intermodal transportation pretended to not limit the analysis to the rail industry itself, but to the industries it is closely connected to. Lastly, although there are limitations present in this thesis, it pretended to contribute to the literature that is still limited in some of the topics, while presenting the factors relevant for the implementation of AI in the industry.

Limitations of the study

A number of limitative factors exist, both related to the literature review and the data collection and analysis. Firstly, the industry that this thesis tries to investigate is heterogenous in its systems and operation, and systems implemented with Artificial Intelligence are still scarce and, combined with the literary review that is still limited in some specific areas, it limited the scope of the investigation and further studies would beneficiate the study of the implementation of AI in the area. Regarding the implementation of AI in intermodal transportation systems being investigated the limitations were similar and further studies would be favorable for the investigation of the impact of these systems.

Lastly, the nature of the data collection also presented limitations, as the two surveys that were completed had a small sample and although country of work of the respondents was diverse, there was a lack of answer from respondent's whose countries have a highly developed rail industry and intermodal terminals. Additionally, the COVID-19 pandemic proved to be a limitation regarding the statistical analysis related to the SEM-PLS approach. Due to the nature of this academic project, time was also a constrain as the long-term study of the implementation of AI in the industry could be beneficial for the study of the impact of its implementation.

Suggestions for future investigations

The mitigation of the limitations above could contribute to future studies that could contribute to the industry or the literature, such as an already mentioned long-term investigation of the effects of Artificial Intelligence systems in the industry. Regarding the data collection, a more heterogenous and bigger sample could be beneficial to the analysis of the sociodemographic factors. The limitations and the effects caused by the COVID-19 pandemic could also be analyzed as well as a comparison and a follow-up with the before and after of an implementation of a system with Artificial Intelligence technologies, that could be beneficial as the customer's opinions could be analyzed along with a discussion from a financial point of view.

To conclude, another suggestion is related to the data analysis tools used that can complement this thesis's analysis and additionally make use of the removal of the sample size limitations of the data collection process. A qualitative approach could also be used in order to investigate exploratory topics or literature gaps or to expand the investigation to complementary systems that use other technologies or are integrated with other areas.

Bibliography

Albalate, D., Bel, G., & Fageda, X. (2015). Competition and cooperation between high-speed rail and air transportation services in Europe. *Journal of Transport Geography*, *42*, 166–174. https://doi.org/10.1016/j.jtrangeo.2014.07.003

Albrecht, A., Howlett, P., Pudney, P., Vu, X., & Zhou, P. (2016). The key principles of optimal train control—Part 2: Existence of an optimal strategy, the local energy minimization principle, uniqueness, computational techniques. *Transportation Research Part B: Methodological*, *94*, 509–538. https://doi.org/10.1016/J.TRB.2015.07.024

Aldabbas, H., Bajahzar, A., Alruily, M., Qureshi, A. A., Amir Latif, R. M., & Farhan, M. (2020). Google Play Content Scraping and Knowledge Engineering using Natural Language Processing Techniques with the Analysis of User Reviews. *Journal of Intelligent Systems*, *30*(1), 192–208. https://doi.org/10.1515/JISYS-2019-0197

Anderson, J. C., & Gerbing, D. W. (1988). Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Bahtizin, A. R., Bortalevich, V. Y., Loginov, E. L., & Soldatov, A. I. (2019). Using artificial intelligence to optimize intermodal networking of organizational agents within the digital economy. *Journal of Physics: Conference Series*, *1327*(1). https://doi.org/10.1088/1742-6596/1327/1/012042

Balster, A., Hansen, O., Friedrich, H., & Ludwig, A. (2020). An ETA Prediction Model for Intermodal Transport Networks Based on Machine Learning. *Business and Information Systems Engineering*, *62*(5), 403–416. https://doi.org/10.1007/S12599-020-00653-0/TABLES/3

Barr, A., & Feigenbaum, E. (1981). *The Handbook of artificial intelligence - Volume 1* (1st ed.).

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research*, *57*(7), 2179–2202. http://10.0.4.56/00207543.2018.1530476

Baykasoğlu, A., Subulan, K., Taşan, A. S., & Dudaklı, N. (2019). A review of fleet planning problems in single and multimodal transportation systems. *Transportmetrica A: Transport Science*, *15*(2), 631–697. https://doi.org/10.1080/23249935.2018.1523249

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing Artificial Intelligence. *MIS Quarterly*, *45*(3), 1433–1450. http://10.0.98.212/MISQ/2021/16274

Bersani, C., Estil-Les, M. A. D. C., & Sacile, R. (2021). Min-Max Approach for High-Speed Train Scheduling and Rescheduling Models. *IEEE Access*, *9*, 41042–41051. https://doi.org/10.1109/ACCESS.2021.3064427

Bersani, C., Estil-Les, M. A. D. C., & Sacile, R. (2021). Min-Max Approach for High-Speed Train Scheduling and Rescheduling Models. *IEEE Access*, *9*, 41042–41051. https://doi.org/10.1109/ACCESS.2021.3064427

Brenna, F., & Foiadelli, D. Z. (2018). *Electrical Railway Transportation Systems*. John Wiley & Sons, Inc. https://doi.org/10.1002/9781119386827

Buchanan, B., Sutherland, G., & Feignenbaum, E. (1969). *Heuristic Dendral: a Program for Generating Explanatory Hypotheses in Organic Chemistry*.

Cacchiani, V., & Toth, P. (2012). Nominal and robust train timetabling problems. *European Journal of Operational Research*, *219*(3), 727–737. https://doi.org/10.1016/J.EJOR.2011.11.003

Cacchiani, V., Caprara, A., Toth, P., Cacchiani, V., Caprara, · A, Toth, · P, Caprara, A., & Toth, P. (2007). A column generation approach to train timetabling on a corridor. *4OR 2007 6:2*, *6*(2), 125–142. https://doi.org/10.1007/S10288-007-0037-5

Cacchiani, V., Jünger, M., Liers, F., Lodi, A., & Schmidt, D. R. (2016). Single-commodity robust network design with finite and Hose demand sets. *Mathematical Programming*, *157*(1), 297–342. https://doi.org/10.1007/S10107-016-0991-9/TABLES/11

Castillo, A. (2021). Natural Language Processing. *CPA Journal*, 16–19.

Catania, C., C., Zanni-Merk, F. D., Beuvron, B. D., & Collet, P. (2015). A Multi Objective Evolutionary Algorithm for Solving a Real Health Care Fleet Optimization Problem. *Procedia Computer Science*, *60*, 255–265.

Chen, J. X. (2016). The Evolution of Computing: AlphaGo. In *Computing in Science and Engineering* (Vol. 18, Issue 4). https://doi.org/10.1109/MCSE.2016.74

Cho, S., Vasarhelyi, M. A., Sun, T. (Sophia), & Zhang, C. (Abigail). (2020). Learning from Machine Learning in Accounting and Assurance. *Journal of Emerging Technologies in Accounting*, *17*(1), 1–10. https://doi.org/10.2308/jeta-10718

Choi, J. J., & Ozkan, B. (2019). Innovation and disruption: Industry practices and conceptual bases. *International Finance Review*, *20*, 3–13. https://doi.org/10.1108/S1569-376720190000020003/FULL/XML

Chow, G. C., & Li, J. (2014). Environmental Kuznets Curve: Conclusive Econometric Evidence for CO2. *Pacific Economic Review*, *19*(1), 1–7. https://doi.org/10.1111/1468-0106.12048

Costa, R., Dias, Á., Pereira, L., Santos, J., & Capelo, A. (2020). The impact of artificial intelligence on commercial management. *Problems and Perspectives in Management*, *17*(4), 441–452. https://doi.org/10.21511/ppm.17(4).2019.36

Cristina, T., Beatrice, C., & Florentina, P. (2008). ARTIFICIAL INTELLIGENCE. *Annals of the University of Oradea, Economic Science Series*, *17*(4), 1532–1536.

Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review: A Journal in Industrial Organization, Innovation and Management Science*, *11*(1), 1. https://doi.org/10.1007/s40821-020-00172-8

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, *173*, 121092. https://doi.org/10.1016/j.techfore.2021.121092

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24–42. https://doi.org/10.1007/S11747-019-00696-0

de Abreu e Silva, J., & Bazrafshan, H. (2013). User Satisfaction of Intermodal Transfer Facilities in Lisbon, Portugal: Analysis with Structural Equations Modeling. https://doi.org/10.3141/2350-12

Dewey, J. (2019). Big data. In *Salem Press Encyclopedia*.

Ding, Y., Sohn, J. H., Kawczynski, M. G., Trivedi, H., Harnish, R., Jenkins, N. W., Lituiev, D., Copeland, T. P., Aboian, M. S., Mari Aparici, C., Behr, S. C., Flavell, R. R., Huang, S.-Y., Zalocusky, K. A., Nardo, L., Seo, Y., Hawkins, R. A., Hernandez Pampaloni, M., Hadley, D., & Franc, B. L. (2019). A Deep Learning Model to Predict a Diagnosis of Alzheimer Disease by Using 18 F-FDG PET of the Brain. *Radiology*, *290*(2), 456–464. https://doi.org/10.1148/radiol.2018180958

Domingos, P., & Lowd, D. (2019). Unifying logical and statistical AI with Markov logic. *Communications of the ACM*, *62*(7), 74–83. https://doi.org/10.1145/3241978

Dong, C., Boute, R., McKinnon, A., & Verelst, M. (2018). Investigating synchromodality from a supply chain perspective. *Transportation Research Part D: Transport and Environment*, *61*, 42–57. https://doi.org/10.1016/J.TRD.2017.05.011

du Toit, C. W., & Bentley, W. (2019). Artificial intelligence and the question of being. *HTS Teologiese Studies / Theological Studies*, *75*(1). https://doi.org/10.4102/HTS.V75I1.5311
Eddison, L. (n.d.). *Deep learning: a technical approach to artificial intelligence for beginners*. 139.
Elleuch, S., Jarboui, B., & Mladenovic, N. (2022). Preventive maintenance planning of railway infrastructure by reduced variable neighborhood programming. *Optimization Letters*, *16*(1), 237–253. https://doi.org/10.1007/S11590-020-01664-2/TABLES/5
Estil-Les, M. D. C., Bersani, C., & Sacile, R. (2020). High-speed train scheduling and rescheduling models. *SOSE 2020 - IEEE 15th International Conference of System of Systems Engineering, Proceedings*, 331–336. https://doi.org/10.1109/SoSE50414.2020.9130554
European Comission. (2006). *Keep europe moving – Sustainable mobility for our continent*. https://www.eea.europa.eu/policy-documents/keep-europe-moving-sustainable-mobility
European Union. (2019). *Commission Implementing Regulation (EU) 2019/773 of 16 May 2019 on the technical specification for interoperability relating to the operation and traffic management subsystem of the rail system within the European Union and repealing Decision*. https://eur-lex.europa.eu/eli/reg_impl/2019/773/oj
Filina-Dawidowicz, L., Możdrzeń, D., & Stankiewicz, S. (2020). Integrated Approach for Planning of Intermodal Food Transport Chains Considering Risk Factors. *Communications in Computer and Information Science*, *1307*, 319–332. https://doi.org/10.1007/978-3-030-62833-8_24
Fraga-Lamas, P., Fernández-Caramés, T. M., & Castedo, L. (2017). Towards the Internet of Smart Trains: A Review on Industrial IoT-Connected Railways. *Sensors (Basel, Switzerland)*, *17*(6). https://doi.org/10.3390/S17061457
Freixo, M. J. V. (2012). *Metodologia científica: fundamentos, métodos e técnicas* (4th ed.).
Gambardella, L. M., Rizzoli, A. E., & Zaffalon, M. (1998). Simulation and Planning of an Intermodal Container Terminal. *Simulation*, *71*(2), 107–116. https://doi.org/10.1177/003754979807100205
Gil, Y., Garijo, D., Khider, D., Knoblock, C. A., Ratnakar, V., Osorio, M., Vargas, H., Pham, M., Pujara, J., Shbita, B., Vu, B., Chiang, Y.-Y., Feldman, D., Lin, Y., Song, H., Kumar, V., Khandelwal, A., Steinbach, M., Tayal, K., … Shu, L. (2021). Artificial Intelligence for Modeling Complex Systems: Taming the Complexity of Expert Models to Improve Decision Making. *ACM Transactions on Interactive Intelligent Systems*, *11*(2), 1–49. https://doi.org/10.1145/3453172
Givoni, M., & Banister, D. (2006). Airline and railway integration. *Transport Policy*, *13*(5), 386–397. https://doi.org/10.1016/j.tranpol.2006.02.001
Göçmen, E., & Erol, R. (2019). Transportation problems for intermodal networks: Mathematical models, exact and heuristic algorithms, and machine learning. *Expert Systems with Applications*, *135*, 374–387. https://doi.org/10.1016/j.eswa.2019.06.023
Gower, B. (1997). *Scientific Method*.
Gupta, M., & Tripathi, S. (2020). Transforming towards a Smarter Supply Chain. *International Journal of Logistics Systems and Management*, *35*(1), 1. https://doi.org/10.1504/IJLSM.2020.10019293
Gupta, S., Modgil, S., Bhattacharyya, S., & Bose, I. (2021). Artificial intelligence for decision support systems in the field of operations research: review and future scope of research. *Annals of Operations Research*, 1. https://doi.org/10.1007/s10479-020-03856-6
Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R*. Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Hair, J., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). *Advanced Issues in Partial Least Squares Structural Equation Modeling* (1st ed.). Sage Publications, Inc.

Harari, Y. N. (2015). *Homo Deus. A brief history of tomorrow*.

Harré, M. S. (2021). Information Theory for Agents in Artificial Intelligence, Psychology, and Economics. *Entropy*, *23*(310), 310. https://doi.org/10.3390/E23030310

Hinde, C. J. (1989). The human-robot interface: The role of artificial intelligence. *International Journal of Production Research*, *27*(3), 463–476. https://doi.org/10.1080/00207548908942560

Hintjens, J., van Hassel, E., Vanelslander, T., & Van de Voorde, E. (2020). Port cooperation and bundling: A way to reduce the external costs of hinterland transport. *Sustainability (Switzerland)*, *12*(23), 1–16. https://doi.org/10.3390/SU12239983

Hong, J. W. (2020). Why Is Artificial Intelligence Blamed More? Analysis of Faulting Artificial Intelligence for Self-Driving Car Accidents in Experimental Settings. *International Journal of Human-Computer Interaction*, *36*(18), 1768–1774. https://doi.org/10.1080/10447318.2020.1785693

Horowitz, M. C., & Kahn, L. (2021). What influences attitudes about artificial intelligence adoption: Evidence from U.S. local officials. *PLoS ONE*, *16*(10), 1–20. http://10.0.5.91/journal.pone.0257732

Hosseini, S., & Barker, K. (2016). Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports. *Computers and Industrial Engineering*, *93*, 252–266. https://doi.org/10.1016/J.CIE.2016.01.007

Huang, P., Wen, C., Fu, L., Lessan, J., Jiang, C., Peng, Q., & Xu, X. (2020). Modeling train operation as sequences: A study of delay prediction with operation and weather data. *Transportation Research Part E: Logistics and Transportation Review*, *141*, 102022. https://doi.org/10.1016/j.tre.2020.102022

Huang, Z., Niu, H., Gao, R., Fan, H., & Liu, C. (2021). Optimizing Train Timetable Based on Departure Time Preference of Passengers for High-Speed Rails. *Journal of Advanced Transportation*, 1–20. http://10.0.4.131/2021/6611289

Huber, L., & Watson, C. (2014). Technology: Education and Training Needs of Older Adults. *Educational Gerontology*, *40*(1), 16–25. https://doi.org/10.1080/03601277.2013.768064

Iannone, F. (2012). The private and social cost efficiency of port hinterland container distribution through a regional logistics system. *Transportation Research Part A: Policy and Practice*, *46*(9), 1424–1448. https://doi.org/10.1016/J.TRA.2012.05.019

International Union of Rails. (2021). *Artificial intelligence Case of the railway sector State of play and perspectives* (Issue March).

Ishfaq, R., & Sox, C. R. (2012). Design of intermodal logistics networks with hub delays. *European Journal of Operational Research*, *220*(3), 629–641. https://doi.org/10.1016/J.EJOR.2012.03.010

Jaakkola. (2020). Artificial Intelligence - Implications for Business Strategy. *MIT Sloan School of Management - MIT Computer Science and Artificial Intelligence Laboratory (CSAIL)*.

Jafarian-Moghaddam, A. R. (2021). Economical Speed for Optimizing the Travel Time and Energy Consumption in Train Scheduling using a Fuzzy Multi-Objective Model. *Urban Rail Transit*, *7*(3), 191–208. https://doi.org/10.1007/s40864-021-00151-w

Janic, M. (2007). Modelling the full costs of an intermodal and road freight transport network. *Transportation Research Part D: Transport and Environment*, *12*(1), 33–44. https://doi.org/10.1016/J.TRD.2006.10.004

Jordan, S. R. (2020). A Costly Emergencies Approach to Estimating Costs for Artificial Intelligence Review. In *2020 IEEE International Symposium on Technology and Society (ISTAS), Technology and Society (ISTAS), 2020 IEEE International Symposium on* (pp. 180–191). IEEE. https://doi.org/10.1109/ISTAS50296.2020.9462212

Khaslavskaya, A., & Roso, V. (2019). Outcome-Driven Supply Chain Perspective on Dry Ports. *Sustainability 2019, Vol. 11, Page 1492*, *11*(5), 1492. https://doi.org/10.3390/SU11051492

Khodadadi, F., Dastjerdi, A. V., & Buyya, R. (2016). Internet of Things: an overview. *Internet of Things: Principles and Paradigms*, 3–27. https://doi.org/10.1016/B978-0-12-805395-9.00001-0

Kishore, P. V. V., & Prasad, C. R. (2017). Computer vision based train rolling stock examination. *Optik*, *132*, 427–444. https://doi.org/10.1016/j.ijleo.2016.12.060

Klumpp, M., & Zijm, H. (2019). Logistics Innovation and Social Sustainability: How to Prevent an Artificial Divide in Human–Computer Interaction. *Journal of Business Logistics*, *40*(3), 265–278. https://doi.org/10.1111/JBL.12198

Kurzweil, R. (1985). What Is Artificial Intelligence Anyway. *American Scientist*, *73*(3), 258.

Lazaridis, A., Fachantidis, A., & Vlahavas, I. (2020). Deep Reinforcement Learning: A State-of-the-Art Walkthrough. Journal of Artificial Intelligence Research, 69, 1421–1471. https://doi.org/10.1613/jair.1.12412

Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Lee, K. J., Kwon, J. W., Min, S., & Yoon, J. (2021). Deploying an Artificial Intelligence-based defect finder for manufacturing quality management. *AI Magazine*, *42*(2), 5. https://doi.org/10.1609/aaai.12001

Li, S., Lv, H., Xu, C., Chen, T., & Zou, C. (2020). Optimized Train Path Selection Method for Daily Freight Train Scheduling. *IEEE Access*, *8*, 40777–40790. https://doi.org/10.1109/ACCESS.2020.2976904

Liebchen, C., & Stiller, S. (2008). Delay resistant timetabling. *Public Transport 2008 1:1*, *1*(1), 55–72. https://doi.org/10.1007/S12469-008-0004-3

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology*, *140*, 44–53.

Lim, L. J., Tison, G. H., & Delling, F. N. (2020). Artificial Intelligence in Cardiovascular Imaging. *Methodist DeBakey Cardiovascular Journal*, *16*(2), 138. https://doi.org/10.14797/mdcj-16-2-138

Liu, S., Wang, Q., & Luo, Y. (2019). A review of applications of visual inspection technology based on image processing in the railway industry. *Transportation Safety and Environment*, *1*(3), 185–204. https://doi.org/10.1093/tse/tdz007

Lorenc, A., & Kuźnar, M. (2021). The most common type of disruption in the supply chain - Evaluation based on the method using artificial neural networks. *International Journal of Shipping and Transport Logistics*, *13*(1–2), 1–24. https://doi.org/10.1504/IJSTL.2021.112910

Maheshwari, S., Gautam, P., & Jaggi, C. K. (2021). Role of Big Data Analytics in supply chain management: current trends and future perspectives. *International Journal of Production Research*, *59*(6), 1875–1900. https://doi.org/10.1080/00207543.2020.1793011

Maity, G., Roy, S. K., & Verdegay, J. L. (2020). Analyzing multimodal transportation problem and its application to artificial intelligence. *Neural Computing and Applications*, *32*(7), 2243–2256. https://doi.org/10.1007/s00521-019-04393-5

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46–60. https://doi.org/10.1016/j.futures.2017.03.006

Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management*, *42*(4), 489–495. https://doi.org/10.1016/j.indmarman.2013.03.001

Meinhart, W. A. (1966). Artificial Intelligence, Computer Simulation of Human Cognitive and Social Processes, and Management Thought. *Academy of Management Journal*, *9*(4), 294–307. https://doi.org/10.2307/254948

Mendes, R. D. (1997). Inteligência Artificial: Sistemas Especialistas No Gerenciamento Da Informação. *Ciência Da Informação*, *26*(1), 39–45. https://doi.org/10.1590/S0100-19651997000100006

Mesquita, C. T. (2017). Artificial Intelligence and Machine Learning in Cardiology - A Change of Paradigm. *International Journal of Cardiovascular Sciences*, *30*(3), 187–188. https://doi.org/10.5935/2359-4802.20170027

Mostafa, S. A., Mustapha, A., Mohammed, M. A., Ahmad, M. S., & Mahmoud, M. A. (2018). A fuzzy logic control in adjustable autonomy of a multi-agent system for an automated elderly movement monitoring application. *International Journal of Medical Informatics*, *112*(November 2017), 173–184. https://doi.org/10.1016/j.ijmedinf.2018.02.001

Nair, R., Avetisyan, H., & Miller-Hooks, E. (2010). Resilience framework for ports and other Intermodal components. *Transportation Research Record*, *2166*, 54–65. https://doi.org/10.3141/2166-07

Naqvi, M. R., Shahzad, S. K., Iqbal, M. W., Ahmed, M., Tahir, M. U., & Khan, B. A. (2020). Need for Computational and Psycho-linguistics Models in Natural Language Processing for Web Documents. *4th International Symposium on Multidisciplinary Studies and Innovative Technologies, ISMSIT 2020 - Proceedings*. https://doi.org/10.1109/ISMSIT50672.2020.9254754

Novikova, S. I., Richman, D. M., Supekar, K., Barnard-Brak, L., & Hall, D. (2013). NDAR: A Model Federal System for Secondary Analysis in Developmental Disabilities Research. *International Review of Research in Developmental Disabilities*, *45*, 123–153. https://doi.org/10.1016/B978-0-12-407760-7.00003-7

O'Brien, M. A., Rogers, W. A., & Fisk, A. D. (2012). Understanding age and technology experience differences in use of prior knowledge for everyday technology interactions. *ACM Transactions on Accessible Computing (TACCESS)*, *4*(2). https://doi.org/10.1145/2141943.2141947

Odijk, M, (1996). A Constraint Generation Algorithm for The Construction Of Periodic Railway Timetables. *Transportation Research Part B: Methodological*, Volume 30, Issue 6, p. 455-464.

Oetjen, J. (2019). Using artificial intelligence in the fight against spam. *Network Security*, *2019*(7), 17–19. https://doi.org/10.1016/S1353-4858(19)30086-8

Pavlenko, V., Pavlenko, T., Morozova, O., Kuznetsova, A., & Voropai, O. (2017). Solving Transport Logistics Problems In A Virtual Enterprise Through Artificial Intelligence Methods. *Transport Problems*, *12*(2), 31–42. https://doi.org/10.20858/tp.2017.12.2.4

Pfoser, S., Treiblmaier, H., & Schauer, O. (2016). Critical Success Factors of Synchromodality: Results from a Case Study and Literature Review. *Transportation Research Procedia*, *14*, 1463–1471. https://doi.org/10.1016/J.TRPRO.2016.05.220

Pyrgidis, C. N. (2021). *Railway Transportation Systems* (3rd ed.). CRC Press. https://doi.org/10.1201/9781003046073

Qu, S., Shi, H., Zhao, H., Yu, L., & Yu, Y. (2021). Research on enterprise business model and technology innovation based on artificial intelligence. *EURASIP Journal on Wireless Communications and Networking*, *2021*(1). https://doi.org/10.1186/s13638-021-02025-y

Quiroz Flores, A., & Pfaff, K. (2021). Private provision of public goods and political survival: Rail transport in four European democracies in the 20th century. *Research in Transportation Economics*, 101046. https://doi.org/10.1016/j.retrec.2021.101046
Rahimova, N. A., & Abdullayev, V. H. (2020). Analysıs of Stages of Development, Current State and Prospects of the Expert Systems. *JITA - Journal of Information Technology and Applications (Banja Luka) - APEIRON*, *19*(1). https://doi.org/10.7251/JIT2001030R
Rahimova, N. A., & Abdullayev, V. H. (2020). Analysıs of Stages of Development, Current State and Prospects of the Expert Systems. *Jita - Journal of Information Technology and Aplications*, *19*(1), 30–34. https://doi.org/10.7251/JIT2001030R
Ruiz-Real, J. L., Uribe-Toril, J., Torres, J. A., & De Pablo, J. (2021). Artificial Intelligence in Business and Economics Research: Trends and Future. *Journal of Business Economics & Management*, *22*(1), 98–117. https://doi.org/10.3846/jbem.2020.13641
Rusca, F., Popa, M., Rosca, E., Rusca, A., Rosca, M., & Dinu, O. (2019). Assessing The Transit Capacity of Port Shunting Yards Through Discrete Simulation. *Transport Problems*, *14*(4), 101–112. https://doi.org/10.20858/TP.2019.14.4.9
Russel, S., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson Education Limited.
Ryan, M. (2020). In AI We Trust: Ethics, Artificial Intelligence, and Reliability. *Science & Engineering Ethics*, *26*(5), 2749–2767. http://10.0.3.239/s11948-020-00228-y
Sanhueza, C., Mendes, A., Jackson, M., & Clement, R. (2020). An efficient genetic algorithm for the train scheduling problem with fleet management. *2020 IEEE Congress on Evolutionary Computation, CEC 2020 - Conference Proceedings*. https://doi.org/10.1109/CEC48606.2020.9185779
Saßmannshausen, T., Burggräf, P., Wagner, J., Hassenzahl, M., Heupel, T., & Steinberg, F. (2021). Trust in artificial intelligence within production management – an exploration of antecedents. *Ergonomics*, *64*(10), 1333–1350. https://doi.org/10.1080/00140139.2021.1909755
Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research Methods for Business Students*.
Schamberger, T., Schuberth, F., Henseler, J., & Dijkstra, T. K. (2019). Robust partial least squares path modeling. *Behaviormetrika 2019 47:1*, *47*(1), 307–334. https://doi.org/10.1007/S41237-019-00088-2
Scheepmaker, G. M., Goverde, R. M. P., & Kroon, L. G. (2017). Review of energy-efficient train control and timetabling. *European Journal of Operational Research*, *257*(2), 355–376. https://doi.org/10.1016/J.EJOR.2016.09.044
Schoenick, C., Clark, P., Tafjord, O., Turney, P., & Etzioni, O. (2017). Moving beyond the Turing Test with the Allen AI Science Challenge. *Communications of the ACM*, *60*(9), 60–64. https://doi.org/10.1145/3122814
Shackman, J. D. (2013). The Use of Partial Least Squares Path Modeling and Generalized Structured Component Analysis in International Business Research: A Literature Review. *International Journal of Management*. https://www.trident.edu/wp-content/uploads/team/pub/40/shackman2013.pdf
Shaw, J., Rudzicz, F., Jamieson, T., & Goldfarb, A. (2019). Artificial Intelligence and the Implementation Challenge. *Journal of Medical Internet Research*, *21*(7), e13659. https://doi.org/10.2196/13659
Shift2Rail. (2021). *About - Shift 2 Rail*. https://shift2rail.org/about-shift2rail/
Singh, A., Wiktorsson, M., & Hauge, J. B. (2021). Trends In Machine Learning To Solve Problems In Logistics. *Procedia CIRP*, *103*, 67–72. https://doi.org/10.1016/J.PROCIR.2021.10.010

Singh, A., Wiktorsson, M., & Hauge, J. B. (2021). Trends In Machine Learning To Solve Problems In Logistics. *Procedia CIRP*, *103*, 67–72. https://doi.org/10.1016/J.PROCIR.2021.10.010

Singh, P., Dulebenets, M. A., Pasha, J., Gonzalez, E. D. S., Lau, Y., & Kampmann, R. (2021). Deployment of Autonomous Trains in Rail Transportation: Current Trends and Existing Challenges. *IEEE Access*. https://doi.org/10.1109/ACCESS.2021.3091550

Šotek, M., Márton, P., Lendel, V., & Lendelová, L. (2021). Investigation of Opinions on the Acceptance of Autonomous Railway Vehicles in Slovakia. *Transportation Research Procedia*, *55*, 1337–1344. https://doi.org/10.1016/j.trpro.2021.07.118

Stacey, J. (2018). *A brief history of the railways*. https://www.raildiscoveries.com/the-discovery-blog/2018/september/a-brief-history-of-the-railways/

SteadieSeifi, M., Dellaert, N. P., Nuijten, W., Van Woensel, T., & Raoufi, R. (2014). Multimodal freight transportation planning: A literature review. *European Journal of Operational Research*, *233*(1), 1–15. https://doi.org/10.1016/j.ejor.2013.06.055

Su, H., Peng, S., Deng, L., Xu, W., & Zeng, Q. (2021). Optimal Differential Pricing for Intercity High-Speed Railway Services with Time-Dependent Demand and Passenger Choice Behaviors under Capacity Constraints. *Mathematical Problems in Engineering*, 1–13. http://10.0.4.131/2021/8420206

Thomas, C. G. (2021). Research Methodology and Scientific Writing. In *Research Methodology and Scientific Writing*. https://doi.org/10.1007/978-3-030-64865-7

Times, G. (2017). *Facial recognition devices installed in central China's Wuhan Railway Station*. http://www.globaltimes.cn/content/1062574.shtml

Towards Data Science. (2018). *How does Machine Learning work?* https://towardsdatascience.com/how-does-machine-learning-work-6dd97f2be46c

Turing, A. (1950). I.—Computing Machinery and Intelligence. *Mind*, *LIX*(236), 433–460. https://doi.org/10.1093/mind/LIX.236.433

United Nations Economic Commission for Europe. (2009). *Illustrated glossary for transport statistics*.

Uno, A., Arai, K., Adachi, K., & Morishima, H. (2020). New Visual Inspection System of Rolling Stock Underside by Image Processing Technique. *JR East*, *19*, 37–40.

Urbas, J. V. (2020). Neural Networks. In *Salem Press Encyclopedia of Science*.

Vellinga, N. E. (2017). From the testing to the deployment of self-driving cars: Legal challenges to policymakers on the road ahead. *Computer Law & Security Review*, *33*(6), 847–863. https://doi.org/10.1016/J.CLSR.2017.05.006

Wang, K., Xia, W., & Zhang, A. (2017). Should China further expand its high-speed network? Consider the low-cost carrier factor. *Transportation Research Part A: Policy and Practice*, *100*, 105–120. https://doi.org/10.1016/J.TRA.2017.04.010

Wienclaw, R. A. (2021). Quantitative and Qualitative Analysis. *Salem Press Encyclopedia*.

Wired. (2018). *A day in the life of a Kiva Robot*. https://www.wired.com/story/ guide-artificial-intelligence/

Wonglakorn, N., Ratanavaraha, V., Karoonsoontawong, A., & Jomnonkwao, S. (2021). Exploring passenger loyalty and related factors for urban railways in Thailand. *Sustainability (Switzerland)*, *13*(10). https://doi.org/10.3390/SU13105517

Woodcock, C., Mittelstadt, B., Busbridge, D., & Blank, G. (2021). The Impact of Explanations on Layperson Trust in Artificial Intelligence-Driven Symptom Checker Apps: Experimental Study. *Journal of Medical Internet Research*, *23*(11), e29386. https://doi.org/10.2196/29386

Yaghini, O., Kelishadi, R., Keikha, M., Niknam, N., Sadeghi, S., Najafpour, E., & Ghazavi, M. (2015). Prevalence of developmental delay in apparently normal preschool children

in Isfahan, Iran. *Iranian Journal of Child Neurology*, *9*(3), 17–23. https://doi.org/10.22037/IJCN.V9I3.7355
Yang, B., Wei, L., & Pu, Z. (2020). Measuring and Improving User Experience Through Artificial Intelligence-Aided Design. *Frontiers in Psychology*, *11*, N.PAG-N.PAG. https://doi.org/10.3389/fpsyg.2020.595374
Yang, J., & Zhao, Q. (2019). Research on Shipping Scheme of Express by High-speed Railway Passenger Train. *Journal of Physics: Conference Series*, *1325*, 12160. https://doi.org/10.1088/1742-6596/1325/1/012160
Yang, K., Wang, R., & Yang, L. (2020). Fuzzy reliability-oriented optimization for the road-rail intermodal transport system using tabu search algorithm. *Journal of Intelligent and Fuzzy Systems*, *38*(3), 3075–3091. https://doi.org/10.3233/JIFS-191010
Yang, P., Cui, D., Dai, X., Lv, Y., Dong, H., Wang, X., & Liu, R. (2021). *A Parallel Intelligent System for Optimizing High-Speed Railway Rescheduling by Learning*. 328–331. https://doi.org/10.1109/DTPI52967.2021.9540209
Yang, S. J., Lee, M. K., & Kim, J. H. (2014). Pricing vulnerable options under a stochastic volatility model. *Applied Mathematics Letters*, *34*(1), 7–12. https://doi.org/10.1016/J.AML.2014.03.007
Yang, X. S. (2009). Firefly Algorithms for Multimodal Optimization. *Lecture Notes in Computer Science*, *5792 LNCS*, 169–178. https://doi.org/10.1007/978-3-642-04944-6_14
Yang, Y. (2020). Analysis of the Impact of Artificial Intelligence Development on Employment. *Proceedings - 2020 International Conference on Computer Engineering and Application, ICCEA 2020*, 324–327. https://doi.org/10.1109/ICCEA50009.2020.00077
Yin, J., Tang, T., Yang, L., Xun, J., Huang, Y., & Gao, Z. (2017). Research and development of automatic train operation for railway transportation systems: A survey. *Transportation Research Part C: Emerging Technologies*, *85*, 548–572. https://doi.org/10.1016/J.TRC.2017.09.009
Yin, M., Li, K., & Cheng, X. (2020). A review on artificial intelligence in high-speed rail. *Transportation Safety and Environment*, *2*(4), 247–259. https://doi.org/10.1093/tse/tdaa022
Zhang, M., Zhang, Q., Lv, Y., Sun, W., & Wang, H. (2018). An AI based High-speed Railway Automatic Train Operation System Analysis and Design. *2018 International Conference on Intelligent Rail Transportation (ICIRT)*, 1–5. https://doi.org/10.1109/ICIRT.2018.8641650
Zhang, Q., & Li, Q. (2020). Research on sea-rail intermodal port capacity optimization based on connection delay. *Proceedings - 2020 5th International Conference on Electromechanical Control Technology and Transportation, ICECTT 2020*, 377–384. https://doi.org/10.1109/ICECTT50890.2020.00090

Annex A – Impact of AI in the rail industry (Survey A)

Artificial Intelligence and the rail industry

The objective of this survey is to try to understand the impact of Artificial Intelligence in the rail industry. In order to do this, in each question a concept is briefly presented and weask you to answer according to your knowledge about the topic in question.

*Obrigat6rio

Artificial Intelligence and the rail industry

Artificial Intelligence has the objective to perform tasks only usually done by humans. Different industries and systems can be implemented with the help of Artificial Intelligence (Al). In the rail industry, Artificial Intelligence can be used ,for example, in train stations , inside trains and to help customers buy tickets.

1. 1 - I am aware of what Artificial Intelligence is *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

2. 2 - I am aware of what Machine Learning is *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

3. 3 - I am aware of the applications of Al and ML in the rail industry *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

4. 4 - The implementation of Al can provide a general competitive advantage to railcompanies *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

5. 5 - There is an economical advantage in implementing Al in the IT systems of railcompanies *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

6. 6 - The implementation of Al can benefit the marketing area and sales of railcompanies *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

7. 7 - Al technologies are sufficiently flexible to adapt to the different areas andsystems in the rail industry *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

8. 8 - The use of Artificial Intelligence allows for more efficient data processing inthe rail industry *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

9. 9 - The implementation of Al systems allows for the reduction of errors in railcompanies *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

10. 10 - The usability of systems in the rail industry is improved with the use of Al *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

11. 11 - Al systems allow rail companies to have better productivity rates *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

12. 12 - The release of new features in rail systems is benefited when Al isimplemented *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

13. 13 - Al systems provide high-quality services and products for the rail industry *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

14. 14 - Al rail systems are more efficient with their operations and logisticprocesses*

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

15. 15 - There is a high implementation cost of Al systems in rail companies *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

16. 16 - Al algorithms and technologies have a bias in the decision-making process *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

17. 17 - The implementation of Al in businesses has a negative effect onemployment *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

18. 18 - There are ethical concerns related to the implementation of Al *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

19. 19 - The implementation of Al presents security concerns *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

20. 20 - I trust Al systems that are implemented in rail companies *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

21. 21 - The implementation time of Al systems are a concern to rail companies *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

22 - User experience is affected when using Al systems *

	1	2	3	4	5	

Do not agree	○	○	○	○	○	Completely agree

23. 23 - Al systems are impacted by the lack of Al experts *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

24. 24 - I trust rail systems integrated with Al technologies *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

25. 25 - The implementation of Al creates a competitive advantage in the railindustry *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

26. 26 - Value creation happens with the implementation of Al in the rail industry *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

Personal Questions

27. Country *

Marcar apenas uma oval.

28. Age *

Marcar apenas uma oval.

c=:) <18

c=) 18-25

c=) 26-35

c=) 36-50

c=) >50

29. Gender *

Marcar apenas uma oval.

c=)

Masculine c=)

Feminine c=)

Outra: ____________________

30. Education Level *

Marcar apenas uma oval.

c=) Elementary school

c=) Intermediate school

c=) High school

c=) Undergraduate degree

c=) Master's degree

c=) PhD

31. Years of Experience in the area *

Marcar apenas uma oval.

(=:) Between O and 1 year

(=:) Between 1 and 2 years

(=:) Between 3 and 5 years

(=:) Between 6 and 10 years

(=:) More than 10 years

Annex B – Impact of AI in intermodal transportation (Survey B)

Artificial Intelligence and lntermodal Systems

The objective of this survey is to try to understand the impact of Artificial Intelligence in the implementation of intermodal system s. In order to do this, in each question a concept is briefly presented and we ask you to answer according to your knowledge about the topic in question.

*Obrigat6rio

Artificial Intelligence and lntermodal Systems

Artificial Intelligence has the objective to perform tasks only usually done by humans. Different industries and systems can be implemented with the help of Artificial Intelligence (Al). In intermodal transportation, Artificial Intelligence can be used in the implementation of the intermodal transportation itself or to allow a better flexiblity in the case of different transport types.

1. 1 - I am aware of what Artificial Intelligence is *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

2. 2 - I am aware of what Machine Learning is *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

3. 3 - I am aware of the applications of Al in passenger intermodal transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	○	○	○	○	○	Completely agree

4. 4 - I am aware of the applications of Al in cargo intermodal transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

5. 5 - Al intermodal transportation can provide a reduction in costs for a company *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

6. 6 - Al intermodal transportation can be adaptable to other means of transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

7. 7 - Al intermodal transportation can be adaptable to have additional companies of thesame type of transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

8. 8 - The use of Al in intermodal infrastructure allows for a better user experience *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

9. 9 - lntermodal systems with Al integration allow for a more efficientinfra-structure monitoring *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

10 - Intermodal AI systems can adapt to system failures *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

11. 11 - AI intermodal transportation can provide better systems standardization *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

12. 12 - Handling efficiency can be positively benefited by intermodal AI systems *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

13. 13 - Tracking efficiency can be positively benefited by intermodal AI systems *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

14. 14 - There is a high cost to implement AI in intermodal transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	O	O	O	O	O	Completely agree

15. 15 - The implementation of AI in intermodal transportation is slow *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

16. 16 - Cargo Loss is a risk in AI intermodal transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

17. 17 - Transfer accidents can happen in AI intermodal transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

18. 18 - The implementation of AI in intermodal transportation can result inloading/unloading delays *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

19. 19 - There is a risk of failure in AI intermodal transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

20. 20 - There are security risks concerning AI intermodal transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

21. 21 - AI intermodal transportation are limited in the type of transportation systems theycan handle *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

22. 22 - AI intermodal systems have difficulties expand to new types of transportation

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

23. 23 - I trust Al freight intermodal transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

24. 24 - I trust Al passenger intermodal transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

25. 25 - A competitive advantage is created with the implementation of Al inintermodal transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

26. 26 - Value creation happens with the implementation of Al in intermodal transportation *

Marcar apenas uma oval.

	1	2	3	4	5	
Do not agree	◯	◯	◯	◯	◯	Completely agree

Personal Questions

27. Country

Marcar apenas uma oval.

28. Age *

Marcar apenas uma oval.

<18

18-25

26-35

36-50

>50

29. Gender *

Marcar apenas uma oval.

Masculine
Feminine
Other

30. Education Level *

Marcar apenas uma oval.

Elementary school In-

termediate school High

school

Undergraduate degree

Master's degree

PhD

31. Years of Experience in the area *

Marcar apenas uma oval.

(=:) Between O and 1 years

(=:) Between 1 and 2 years

(=:) Between 3 and 5 years

(=:) Between 6 and 10 years

(=:) More than 10 years

Annex C – Relation between hypothesis, indicators and literature for RQ2

Variables	Indicators	Questionnaire Questions
Benefits of implementing AI in the rail industry	Economical competitive advantage (Martínez-López and Casillas, 2013; Costa, 2020)	The implementation of AI can provide a general competitive advantage to rail companies
		There is an economical advantage in implementing AI in the IT systems of rail companies
		The implementation of AI can benefit the marketing area and sales of rail companies
	Environmental Adaptation (Russell and Norvig, 2021)	AI technologies are sufficiently flexible to adapt to the different areas and systems in the rail industry
	Data processing efficiency (Gil et al., 2021)	The use of Artificial Intelligence allows for more efficient data processing in the rail industry
	Error reduction (Lim et al., 2020)	The implementation of AI systems allows for the reduction of errors in rail companies
	User adaptability (Yang et al., 2020)	The usability of systems in the rail industry is improved with the use of AI
	Productivity gains (Damioli et al., 2021)	AI systems allow rail companies to have better productivity rates
	Feature innovation (Qu et al., 2021)	The release of new features in rail systems is benefited when AI is implemented
	System Quality (Lee et al., 2021)	AI systems provide high-quality services and products for the rail industry
	Operations and processes efficiency (Gupta et al., 2021)	AI rail systems are more efficient with their operations and logistic processes
	Cost Implementation (Jordan, 2020)	There is a high implementation cost of AI systems in rail companies

Variables	Indicators	Questionnaire Questions
Risks of implementing AI in the rail industry	Biased decision making (Russell and Norvig, 2021)	AI algorithms and technologies have a bias in the decision-making process
	Impact on employment (Harari, 2015; Yang, 2020)	The implementation of AI in businesses has a negative effect on employment
	Ethical doubts (Berente et al., 2021)	There are ethical concerns related to the implementation of AI
		The implementation of AI presents security concerns
	Implementation time (Shaw et al., 2019)	The implementation time of AI systems provide concern to rail companies
	HCI issues (Russell and Norvig, 2021)	User experience is affected when using AI systems
	Shortage of AI experts (Russell and Norvig, 2021)	AI systems are impacted by the lack of AI experts
Trust in AI in the rail industry	Trust in AI rail systems (Wonglakorn et al., 2021)	I trust AI corporate systems
		I trust rail systems integrated with AI technologies
Impact of AI in the rail industry	Interest in implementing AI in the rail industry	The implementation of AI creates a competitive advantage in the rail industry
		Value creation happens with the implementation of AI in the rail industry

Annex D - Relation between hypothesis, indicators and literature for RQ3

Variables	Indicators	Questionnaire Questions
Benefits of AI Intermodal transportation	Cost Savings (Singh et al., 2021)	AI intermodal transportation can provide a reduction in costs for a company
	Flexibility (Singh et al., 2021)	AI intermodal transportation can be adaptable to other means of transportation
		AI intermodal transportation can be adaptable to have additional companies of the same type of transportation
	Better user experience (de Abreu e Silva & Bazrafshan, 2013)	The use of AI in intermodal infrastructure allows for a better user experience
	Monitoring efficiency (Balster et al., 2020)	Intermodal transportation with AI integration allow for a more efficient infrastructure monitoring
	Failure Adaptability (Bahtizin et al., 2019)	Intermodal AI systems can adapt to system failures
	System Standardization (EU, 2019)	AI intermodal transportation can provide better systems standardization
	Handling efficiency (Pfoser et al., 2016)	Handling efficiency can be positively benefited by intermodal AI systems
	Tracking efficiency (Pfoser et al., 2016)	Tracking efficiency can be positively benefited by intermodal AI systems
Risks of AI Intermodal transportation	Implementation Cost (Givoni & Banister, 2006; Wang et al., 2017)	There is a high cost to implement AI in intermodal transportation
	Implementation Time (Ishfaq & Sox, 2012)	The implementation of AI in intermodal transportation is slow

Variables	Indicators	Questionnaire Questions
	Cargo Loss (Filina-Dawidowicz et al., 2020; Hintjens et al., 2020; Lorenc & Kuźnar, 2021)	Cargo Loss is a risk in AI intermodal transportation
	Transfer Accidents(Janic, 2007)	Transfer accidents can happen in AI intermodal transportation
	Loading/Unloading Delays (Zhang & Li, 2020)	The implementation of AI in intermodal transportation can result in loading/unloading delays
	System failure (Dong et al., 2018; Hosseini & Barker, 2016)	There is a risk of failure in AI intermodal transportation
	Security concerns (Nair et al., 2010)	There are security risks concerning AI intermodal transportation
	Expandability concerns (Iannone, 2012)	AI intermodal transportation are limited in the type of transportation systems they can handle
		AI intermodal systems have difficulties expand to new types of transportation
Awareness of AI in intermodal transportation	Awareness of AI technologies (Horowitz & Kahn, 2021; Gambardella et al., 1998)	I am aware of what AI is
		I am aware of what ML is
		I am aware of the applications of AI in passenger intermodal transportation
		I am aware of the applications of AI in cargo intermodal transportation
Trust in AI Intermodal transportation	Trust in AI freight intermodal transportation (Rusca et al., 2019)	I trust AI freight intermodal transportation
	Trust in AI passenger intermodal transportation (Wonglakorn et al., 2021)	I trust AI passenger intermodal transportation

Variables	Indicators	Questionnaire Questions
Impact of AI in intermodal transportation	Interest in implementing AI in intermodal transportation	A competitive advantage is created with the implementation of AI in intermodal transportation
		Value creation happens with the implementation of AI in intermodal transportation