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The Implementation of Artificial Intelligence in the automotive sector: incidence and relationship with corporate performance and strategy

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摘要

該分析的重點是研究人工智能的實施如何影響汽車行業的關鍵企業績效變量。更具體地說，該研究將分析人工智能實施與企業績效和戰略之間的發生率和關係。以前從未有學者研究過這些關係。此外，本文將展示對早期報告中研究的主題的當前研究。

具體而言，本研究的目的是回答以下研究問題：1） 人工智能的實施與汽車行業的企業績效之間是否存在關係？ 2) 企業財務績效與人工智能在汽車行業的實施在多大程度上相關？ 3) 企業社會責任在多大程度上與人工智能在汽車行業的實施相關？ 4) 人工智能在汽車行業企業合併戰略的基礎上實施到什麼程度？

為了闡述我的假設，我收集了在汽車行業運營的公司樣本，並檢查了人工智能實施與企業財務績效和企業社會責任之間的聯繫。此外，我還研究了人工智能實施與公司合併戰略之間的關係。

分析是通過多元線性回歸模型進行的。

分析結果從經驗上表明，人工智能與企業績效、企業財務績效、企業社會責任和公司合併戰略呈正相關。

關鍵詞：人工智能；企業績效；公司財務業績；企業社會責任；合併戰略。

Abstract

This analysis focuses on studying how the implementation of Artificial Intelligence has affected key corporate performance variables within the automotive industry. More specifically the study will analyse the incidence and relationship between AI implementation and corporate performance and strategy.
It has never happened before that scholars investigated these relationships.
Furthermore, this paper will demonstrate a current study of the subject examined in earlier reports.
Specifically, the purpose of this study is to answer the following research questions: 1) Is there a relationship between the implementation of Artificial Intelligence and Corporate Performance in the automotive industry? 2) To what extent is Corporate Financial Performance related to the implementation of Artificial Intelligence in the automotive industry? 3) To what extent is Corporate Social Responsibility related to the implementation of Artificial Intelligence in the automotive industry? 4) To what extent is the implementation of Artificial Intelligence at the basis of Companies' Merged Strategy between automotive industries?
In order to text my hypotheses, I collected a sample of firms operating in the automotive sector and I examined the link between AI implementation and Corporate Financial Performance and Corporate Social Responsibility. In addition, I examined the relationship between AI implementation and Companies' Merged Strategy.
The analysis is conducted through multiple linear regression models.

The outcomes of the analysis demonstrate empirically that AI is positively correlated with Corporate Performance, Corporate Financial Performance, Corporate Social Responsibility and Companies' Merged Strategy.

Keywords: Artificial intelligence; Corporate Performance; Corporate Financial Performance; Corporate Social Responsibility; Merged Strategy.

1. Introduction

The aim of this thesis is to analyze how the implementation of Artificial Intelligence within the automotive industry has affected key corporate performance variables. More specifically, I intend to analyze how, in the aftermath of the pandemic, companies have used the new technologies to recover from cost increases in the face of reduced sales, and how they are the basis of mergers and acquisitions between companies to achieve a redistribution of costs across multiple businesses.

Specifically, the purpose of this study is to answer the following research questions: 1) Is there a relationship between the implementation of Artificial Intelligence and Corporate Performance in the automotive industry? 2) To what extent is Corporate Financial Performance related to the implementation of Artificial Intelligence in the automotive industry? 3) To what extent is Corporate Social Responsibility related to the implementation of Artificial Intelligence in the automotive industry? 4) To what extent is the implementation of Artificial Intelligence at the basis of Companies' Merged Strategy between automotive industries?

In order to test the hypotheses, I divide my project into three different sections.

In the first section, I will introduce the concepts of Corporate Performance, Corporate Financial Performance and Corporate Social Responsibility, which identify the company and provide a comprehensive assessment.

Subsequently, I will provide an overview of the current landscape, which features the advent of Industry 4.0 and the new Smart Factory. Specifically, I will focus on the discovery of Artificial Intelligence and new industrial technologies, providing an overview of the status of industries regarding its implementation.

Besides, I will outline the key consequences that affected the automotive sector as a result of Covid-19 and the reason why automotive companies increase their AI investments. In fact, the automotive sector has been suffering losses since the early stages of the outbreak - when the supply chain effects originating in China began to spread globally. In addition to the production stoppage, the sector was also hit especially hard on the supply and demand side. The Coronavirus disrupted global supply chains, exposing weak links in the chains to the greatest consequences, and exposed many consumers to uncertainty in the months ahead, who consequently postponed or cancelled the purchase of a new car. As a result of declining vehicle ownership and volume, car manufacturers will have to adapt to meet and fully restore demand. This will require smarter production methods and factories to reduce costs and maintain a viable profit margin. The use of AI to dictate supply chain management, along with the use of intelligent robots in factories, will go a long way in reducing costs in the long run, despite the initial capital expenditure required to implement the technology.

The reason for the growing importance of AI is due to the increasing homogenization of mobility vehicles. This means that, in the future, consumers will get used to prioritizing vehicle function over form. They will not choose the best vehicle, but the best service, and AI will help provide the best services. AI is, therefore, a crucial tool to capitalize on this over-premiumization of function over form.

In addition, I will illustrate the theory of AMC to illustrate the relationship between alliance management capability and the redistribution of costs for incurring R&D costs related to AI implementation. The theory argues that alliance management between companies can take place on one or more projects within the B2B context, i.e., concerning information exchange, context and needs assessment of capabilities analysis, resource mobilization, joint risk assessment or sharing of logistical facilities.

In the second section, I will collect a panel of companies operating in the automotive sector and reformulate their Balance Sheets and Income statements for the last fiscal year, 2021 (source: Refinitiv Workspace, 2021), in order to obtain evidence on 1), 2) and 3) research questions. By identifying the key parameters expressing the impact of AI adoption in terms of profitability and social responsibility, through multiple linear regression (software: SPSS Statistics), I will draw a multiple regression to examine my hypotheses.

In addition, I will collect a panel of major automotive groups to test 4) research question, for which I assume that the underlying reasons lie in the distribution of R&D costs (related to the implementation of AI) across multiple companies. I have collected data from 2017 to 2021, to highlight how over the past few years, companies are increasingly deciding to merge and share R&D costs related to AI implementation.

In the last section I will analyze the results obtained and identifying the nature and incidence of the reports on the research questions mentioned above, showing the empirical evidence of the nature of the incidence of AI implementation.

2. Literature Review

To investigate the impact resulting from the implementation of Artificial Intelligence on Corporate Performance and Companies' Merged Strategy in the automotive industry, this section examines what scholars have found on these topics, introducing the idea behind the hypothesized relationship.
First, I introduce the concepts of Corporate Performance and how it is subdivided into Corporate Financial Performance and Corporate Social Responsibility.
Next, I outline the automotive industry, the consequences of Covid-19 on the sector, the implementation of Artificial Intelligence and its envious correlation with Corporate Performance. Third, I conclude by examining the incidence and impact of AI on Corporate Performance and Companies' Merged Strategy, to arrive at demonstrating the studies done on the automotive sector.

2.1 Corporate Performance

The highly dynamic environment in which companies compete has led scholars over the years to revisit and reformulate the concept of corporate performance.
In the late 1970s, multidimensional models of corporate performance measurement began to emerge, which shifted the focus to a dimension of analysis that was not just financial. In this regard, the simple reading and analysis of financial statements, used to determine financial-economic indicators, had proved insufficient in capturing all the determinants necessary for the complete assessment of corporate performance (Olivotto, 1995).
Economic-financial indicators were unable to provide assessments related to intangible assets, for example human capital, necessary for the identification of the best strategies to achieve the best performance of the business model, which can pursue positive and sustainable results in the long term (Kaplan & Norton, 2005).
These multidimensional assessment models have evolved and subsumed over time because of events that have changed the world scenario over the years to the present day. In 1987, World Commission on Environment and Development (WCED) published the so-called Brundtland Report, through which the concept of sustainable development was defined and introduced, defined as "development that enables the

present generation to meet its needs without compromising the ability of future generations to meet their own needs". For the first time, attention was beginning to be paid to the environment and the consequent concept of environmental sustainability, the preservation and protection of which is a matter of common concern and must be a commitment on the part of businesses, institutions and individuals.

Hence, companies began to become aware of their fundamental role in promoting sustainable development, implementing the latter in corporate governance to lead management to voluntarily assume, in the choices to be made, a form of responsibility toward social stakeholders and the surrounding environment (Sacconi, 2003).

Thus, the old concept of governance based on the "shareholder value" model has been replaced by a new way of doing business, with companies aware that the central role assumed by the "responsible consumer" in the globalized economy. In the current scenario, most companies to have adopted governance on the "stakeholder value" model, according to which the creation of value by companies is not only directed toward satisfying the interests of equity holders (shareholders), but is oriented toward all stakeholders to the company, whether external or internal to it. Stakeholders are those individuals who possess a qualified interest, whether competitive or cooperative, including not necessarily economic, in the company's activities (Evan & Freeman, 1988).

In conclusion, for the evaluation of corporate performance, in agreement with the students, it is appropriate to apply a multidisciplinary model whereby alongside economic responsibility, a corporate environmental and social responsibility is outlined (Chirieleison, 2001).

2.1.1 Corporate Financial Performance

Scholars have always used corporate performance as a tool to define the current development and potential growth level of an organization.

Corporate financial performance refers to the ability of a company to generate revenue using its assets and is one of the main indicators used to assess the overall health of the company. Stakeholders are linked to performance and, consequently, interested in management's financial ability to exploit its assets and manage its properties.

CFP represents the degree to which a company is able to achieve its economic and financial objectives (Venkatraman and Ramanujam, 1986). Therefore, it is crucial for companies to achieve their objectives both from an operational and monetary perspective (Agola, 2014).

Corporate Financial Performance defines competitiveness, the economic potential of the business and the management interests of the company (Dufer, 2010).

A good financial performance rewards shareholders in terms of return on their investment and is the key benchmark indicator for all stakeholders in corporate fortunes. (Ongore and Gemechu, 2013).

CFP can be measured by various financial measures such as profit after tax, Return on Assets (ROA), Return on Equity (ROE), Return on Capital Invested (ROIC), earnings per share and Debt to Equity Ratio (Yeneew, 2014).

ROE is considered the indicator par excellence and the one that is most often considered. The higher the ROE, the better the company's overall financial performance.

Conversely, a high Debt to Equity Ratio means a higher dependence of the company on external creditors and consequently a higher debt burden (Mindra and Erawati, 2014).

These are only some of the indicators used for a proper CFP assessment. Financial KPIs, apart from being the main indicators used and considered by stakeholders to define their investment choices, are also heavily used by business leaders. By means of KPIs, internal stakeholders can govern and monitor the company's performance, define possible problems and target areas, and, in come, use them to achieve and predetermined goals (Baraza, 2014).

Financial KPIs are divided into five categories:

Profitability KPI: indicates the company's ability to generate profit i.e., gross profit margin and net profit margin.

Liquidity KPIs: assess the company's ability to pay for its properties in the short and long term, i.e., current ratio and quick ratio.

Efficiency KPIs: indicate how efficiently the company is allocating and deploying its resources, i.e., inventory turnover and receivables turnover.

Valuation KPIs: estimate the market value of the company i.e., earnings per share and price/earnings ratio.

Leverage KPIs: assess the degree to which the company is dependent on external sources of finance, i.e., debt/equity and debt-to-equity ratio.

2.1.2 Corporate Social Responsibility

The meaning of Corporate Social Responsibility is a widely discussed topic in the literature and has its roots in the Berle-Dodd debate of the 1930s. The controversy concerns the role played by companies, whether they should merely play an economic role or be an integral part of society (Bratton & Wachter 2008).

One of the earliest definitions of CSR dates back to 1950 and associated the term 'social responsibility' with the incorporation of stakeholders and their interests into the way companies are managed. Bowen (1953) identified the social duties that the company had to incorporate in order to protect the welfare of employees and the general public (Carroll 1999).

CSR began to be regulated from the 1970s onwards, when regulations on the environment, worker safety and the protection of consumers and all those connected with the company were introduced.

Despite this, to this day CSR is still interpreted in various ways in the literature, and we can distinguish three main meanings: i) "CSR as mere compliance with existing laws and market demands" (Kerr, 2008); ii) CSR as "beyond compliance" (Rosen-Zvi, 2011); iii) CSR as "companies sharing responsibility for social conditions" (Jackson, 2010).

The first usage refers exclusively to the mere alignment of CSR government regulation to ensure that companies do not generate excessive and negative externalities for society and focusing on satisfying the interests of shareholders and stakeholders (Strine, 2012).

The second use requires CSR to be understood as a voluntary action on the part of the company aimed at self-regulation (Rana, 2014). This approach above companies to go beyond mere regulatory compliance and beyond maximizing shareholder value Companies must go beyond the law and commit to environmental protection, labor rights, human rights, and community development. The interests to be protected must correspond to those of all stakeholders, not just shareholders (Lin, 2010).

The third meaning takes a stakeholder-oriented view but does not refer to the concept of acting beyond compliance.

In the 21st century, the focus has shifted to the concepts of environmental, social and governance (ESG) 'sustainability'. The term ESG does not only refer to environmental, social and governance sustainability measures, but also refers to all non-financial values that can affect financial performance i.e., corporate governance, labor standards, human capital management and environmental protection (Harper, 2016).

The term ESG coincides with the second meaning of CSR, as it implies an additional commitment on the part of the company. ESG considers compliance, environmental, regulatory, operational, and strategic risks.

However, the boundaries of these terms, ESG and CSR, are not entirely precise and are often used interchangeably. The literature has shown that investing in ESG is mainstream for companies (Goldman Sachs, 2016). ESG investigation strategies reflect positively on corporate social responsibility, including its governance structure, social and environmental impact (Schanzenbach & Sitkoff 2019).

Furthermore, CSR is best measured by the MSCI ESG - Environment, Social and Governance index. The ESG breaks down CSR into three aspects and highlights its quality standards regarding environmental, social and governance issues (SustainAbility, 2020).

2.2 Evolution of Industry 4.0 and Smart Factory

The Fourth Technological Revolution is affecting the entire society, the new generations, the economic and social system, and the environment in general. It involves cyber-physical systems, i.e., the progressive implementation of technologies such as Artificial Intelligence, Blockchain, Genomics and the Internet of Things (CPS; Maynard, 2015; Schwab, 2017).

The current industrial revolution differs from previous ones in several respects, both in terms of disruptive technologies and labor. In the first case, the new industry focuses on Artificial Intelligence involving machine learning and new intelligent processors (Dunjko & Briegel, 2018). Secondly, Artificial Intelligence is enabling wealth creation by reducing marginal costs, by placing intelligent digital systems alongside the

workforce that can optimize the resources employed (Goldfarb & Tucker, 2019; Schwab, 2017).
Parallel to the advent of the Fourth Industrial Revolution and new interconnected systems, companies are also evolving towards the so-called Smart Factory.
The literature provides different interpretations regarding the new evolution of industry. The Smart Factory is seen as an open network that allows, through IT capabilities, elements to interact and act independently, giving overall greater flexibility to the corporate structure (Wilkesmann, 2018).
The essential prerequisite for the Smart Factory is Artificial Intelligence, which constitutes an integrated intelligence in all devices, enabling a modular structure (Zuehlke, 2018).
Overall, the Smart Factory can be defined as a manufacturing solution that ensures flexibility and adaptability of production processes, making them more dynamic and able to adapt to a changing environment. Artificial Intelligence and the Internet of Things lead companies to a decentralized supply - chain, in which the set of interconnected intelligent structures enables a larger market area to be covered (Radziwon, 2014).

2.2.1 Artificial Intelligence

According to the IEEE Neural Networks Council, Artificial Intelligence is defined as "the study of how to make computers do things that, at the moment, people are better at" (Rich, Knight,1990).
Since 1998, Artificial Intelligence (AI) has gained ground in contemporary society and business realities, becoming the subject of study by technology, consulting, and business organizations. Specifically, AI corresponds to the replication of human analytical and decision-making capabilities (Finlay, 2018). AI is divided into three macro categories: Narrow AI includes applications and algorithms that can replicate actions and what is happening (Burgess, 2018)., General AI consists of replicating human capabilities in an intelligent way (Finlay, 2018)., and finally, Super AI is able to replicate human capabilities and surpass them (Kaplan & Haenlein, 2019).
The rise and success of AI can be attributed to the centrality of Big Data, low-cost storage, Internet connectivity, Machine Learning, and Could AI. These technologies

have been instrumental in the advancement and implementation of AI in everyday business realities, thus influencing society (Burgess, 2018).

The fundamental components of AI are:

- *Machine Learning (ML):* machine learning corresponds to the area of AI that allows computers to learn and process without explicit programming, that is, it focuses on developing programs that change with the introduction of new data. Machine learning is divided into supervised and unsupervised algorithms, depending on whether or not the algorithm itself depends on the definition of a target variable.

In the first case, supervised learning is mainly used to predict numerical values (regression) and for classification purposes by identifying known input variables (predictors) and target value (labels). This data set is called training data and is used for object, facial and voice recognition, credit evaluation and customer abandonment. The capability lies in the fact that the algorithms are of degrees to determine continuous numerical values based on multiple input variables.

In the second case, unsupervised learning is used to identify relationships between individual data and group them into clusters. Consequently, this process does not depend on individual target variables but, instead, uses a dataset in general. Unsupervised learning is used to identify groups of customers based on their buying behavior, demographics, and preferences.

In contrast to static that follows a sample-based approach, Machine Learning is critical for formulating dynamic solution strategies and optimization.

- *Computer Vision (CV):* is a field of AI research involving scientific theories from different fields of study, such as biology, neuroscience, computer science, physics and mathematics. The main goals of VC consist of the reconstruction of a scene and how it is observed, the emulation of biological visual perception, and the subsequent technical development for problem solving through the development of efficient algorithms. These goals correspond to three distinct research areas that overlap and influence each other.

This technology is used in new cars, for example, to identify an obstacle and initiate automated braking in case of danger. In this case, the CV is responsible for extracting from the image the information relevant to the specific task and processing a timely response. CV considers a set of fixed features, which combined with set algorithms manage to identify optimal solutions by prior identification of geometric parameters, such as scaling, translation, and rotations.

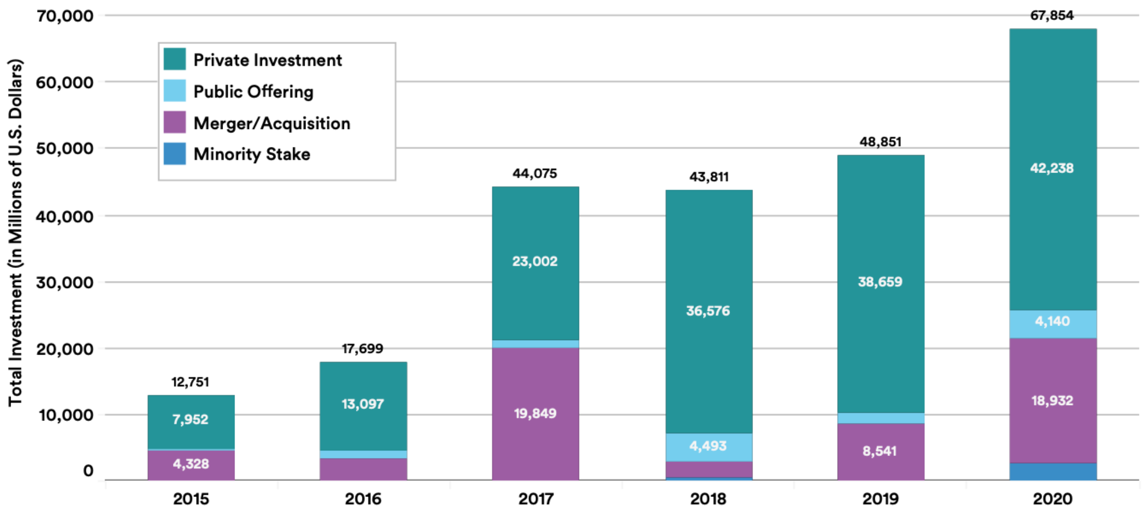
- *Knowledge Representation & Reasoning (KRR):* this section of AI constitutes the research field related to the reproduction of human cognitive abilities. KRR focuses on the design of inference algorithms, i.e., capable of finding answers based on data without human assistance.
Inference constitutes the decision-making process focused on processing answers related to activity preference. These answers are processed and taken quickly as they come from a dynamic domain that changes over time. A simple example of KRR is autonomous driving, the presence of which algorithms can process responses and adapt to road and traffic changes in a timely manner.
- *Language and Communication:* in the field of AI, language is fundamental, and we distinguish between computational linguistics (CL) and natural language processing NLP). The former focuses on the use of computers for processing purposes, while the latter includes machine translation (MT) of questions and answers. Specifically, NLP includes tagging parts of speech, natural language understanding and generation, summarization and MT, sentiment analysis, relation extraction, and morphological segmentation.
Consequently, this process involves information retrieval (IR), which groups texts according to content, and information extraction (IE), which finds items to answer questions in the text. On a practical level, this method is implemented in the automobile to ensure interaction between the user and the system.
Artificial Intelligence thus transforms the industrial landscape, supply chains and product design itself, holding the potential to mimic the cognitive, emotional and social intelligence of humans, with the exception of only artistic creativity (Kaplan & Haenlein, 2019).

2.2.2 AI Corporate Investment

Despite the recession caused by the Covid-19 pandemic, companies have not stopped investing in AI. On the contrary, as reported by the Artificial Intelligence Index Report 2021, the global investment in AI increased by 40 per cent compared to 2019, totaling about USD 68 billion. The investment growth involved private investments, public offerings, mergers and acquisitions and minority stakes. In particular, the pandemic led companies to increase M&A activity, which is the main source of investment in AI.

Compared to 2019, mergers and acquisitions increased by 121.7 per cent in AI investments (AI Index Steering Committee, 2021).

Table 1: Global Corporate Investment in AI

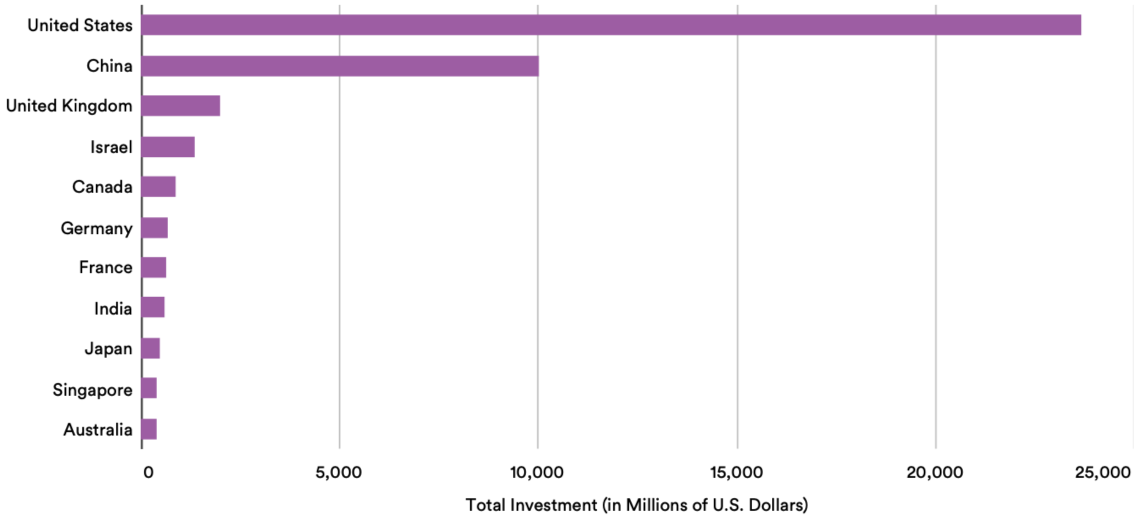


Source: Artificial Intelligence Report 2021

Geographically, as can be seen from the graph below, investments in AI are mainly driven by the United States ($23.6 billion), followed by China ($9.9 billion) and the United Kingdom ($1.9 billion).

In particular, the United States enjoys a favorable position for private investment, while China, on the other hand, has large public investments in AI. Both central and local governments in China are spending heavily on research and development.

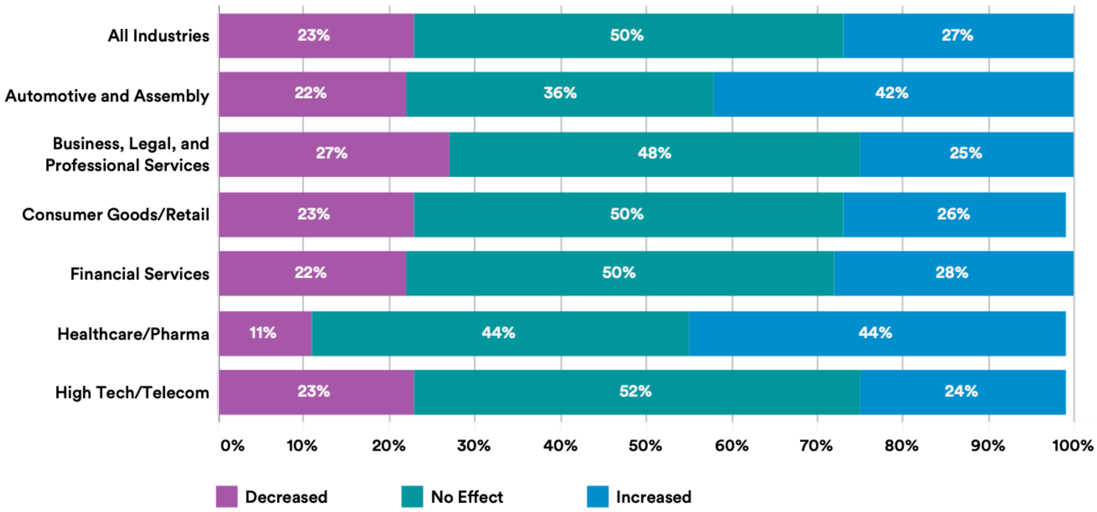
Table 2: Investment in AI by Country



Source: Artificial Intelligence Report 2021

At the market level, the industries that have invested the most in AI are shown in the graph below. In particular, in the face of the pandemic, companies in the healthcare and pharmaceutical sectors, as well as automotive and assembly, were the most likely to increase their investments in AI.

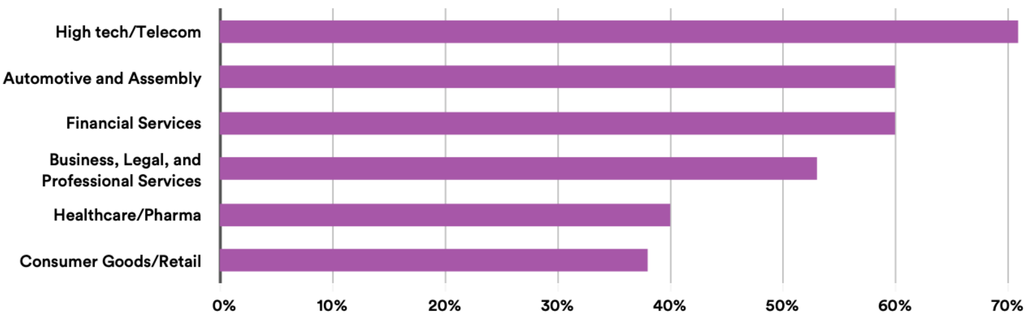
Table 3: Changes in AI Investments amid the Covid-19 Pandemic



Source: Artificial Intelligence Report 2021.

By function, as reported by the Artificial Intelligence Report 2021, the automotive and assembly industries record a higher adoption of AI related to manufacturing functions. Financial services companies report a high degree of AI implementation in support of risk functions.
Technology and telecommunications companies report higher AI adoption for product and service development functions.

Table 4: AI Adoption by Industry



Source: Artificial Intelligence Report 2021.

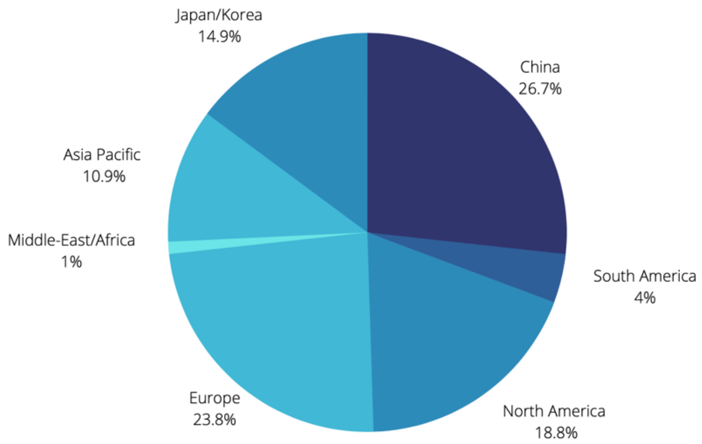
2.3 Automotive Industry

The automotive industry is one of the driving sectors for the global economy and its profitability.
According to data reported at the end of 2019, at the dawn of the pandemic outbreak, the automotive industry accounted for 7% of GDP in the EU, 3.5% of GDP in the US and 10% of GDP in China.
At the same time, the industry employed around 27 million people, 14 million in Europe, 8 million in the US and 5 million in China, and the automotive industry contributed to the growth and maintenance of other sectors with which it shares the value chain, such as "upstream" (i.e., steel, chemicals, textiles) and "downstream" (i.e., repair, mobility services) companies (Accenture, 2020).

2.3.1 Progress in scaling AI by Companies

When the Coronavirus began to manifest itself in Wuhan, China, the consequences were also brutally felt in the automotive market. In fact, when China decided to proceed with a period of population isolation, all major international car manufacturers were exposed to disruption of supply flows, China being the leading country for the sector globally, as a market and for the industrial reality it represents (Debernardis, 2020).

Table 5: Automotive Market by Country



Source: Personal elaboration, OICA, 2020

From the graph above, the production stoppage in China has had global consequences, both in terms of output and employment. This was since the global automotive industry is highly interlinked and interdependent, with the closure of one plant having consequences for the global supply chain.

In fact, China is the largest producer of cars produced in 2019, accounting for around 25% of the total 90 million produced. The around other 25% corresponds to the total production of Germany, France, the UK, Italy and Spain.

According to the OICA, in 2020, cars' production decreased by 16%, equivalent to 78 million vehicles. European countries recorded losses of between 11% and 40%, or 22% overall. U.S. countries recorded a drop in production of 19% and Brazil 32%.
Most affected was the African continent, recording a drop equivalent to 35%.
On the other hand, China, where the crisis originated, was able to react quickly, accounting for a drop in production of only 2%; Asia maintained around 50% of world production during the crisis (OICA, 2021).
As the pandemic has progressed, the global dimension with which this health emergency is impacting the automotive industry has become increasingly evident.
In addition to the economic and social damage illustrated above - a drop in sales and volumes produced, as well as an increase in the unemployment rate linked to the sector - Covid-19 has highlighted weaknesses in various areas of the value chain. Indeed, the shock to the international supply chain has highlighted difficulties in sourcing components that are essential to assembly and the smooth running of production activities, as well as the restriction of the consumer base and the need to replan investments in the face of uncertainty about future sales trends (Deloitte, 2020).
Against this difficult and uncertain backdrop, automakers have found themselves challenged to define mobility in the immediate present and future.
To remain competitive, companies have had to cut costs and rationalize the value chain to recover cash and redeploy it into profitable investments that ensure global manufacturing continuity.
During the pandemic, when supply chains came to a halt and dealerships were closed, technology became critical and valuable, and while it was previously considered ancillary and marginal in our daily lives, it is now an integral part of reality.
Technology has not only improved and enabled the interaction and buying experience for the customer, but in general, it has brought greater transparency and efficiency along the supply chain.
The automotive industry is increasingly entering the CASES (Connectivity, Autonomous Driving, Sharing-Mobility, Electrification, Servitization) world, towards which automotive companies have already invested more than $300 billion* since 2010 McKinsey Quarterly, 2021).
The largest investments made in recent years and in response to the pandemic are converging towards emerging Artificial Intelligence (AI) and connectivity technologies, namely 5G telecommunications in vehicles. It is important to note how

automakers are deploying these smart technologies in both electric vehicles (EVs) and traditional vehicles (ICEs).
Automotive companies are harnessing the full potential of the Fourth Industrial Revolution (4IR) to achieve a more holistic approach of different activities, from design-studio to factory and finally to showroom.
Companies are moving towards a new reality where vehicles, manufacturers, and cities themselves are interconnected. This continuing evolution will result in the convergence of the automotive sector with the technology sector (PwC, 2020).
As new players enter the industry, automotive companies will need to prepare an appropriate strategic plan that combines AI with capital and workforce structures, as well as choose between bringing new technology competitors into their supply chains or developing comparable capabilities in-house.

2.3.2 New conception of car: from product to service

In years past, automakers compared and competed through their engineering capabilities; today, the auto industry is no longer focusing its resources on developing superior driving performance over the competition but is turning its attention to the customer experience. The orientation adopted is customer-centric, i.e., it is directed towards the fullest and most complete, as well as satisfying, customer experience ranging from the pre-purchase moment to the purchase process and the post-purchase experience.
This new mindset is becoming an integral part of both OEMs (Original Equipment Manufacturers) and auto dealers, who must constantly think about what customers want and when they want it (Berger, 2018).
At the same time, consumer preferences have changed dramatically; Google estimates that more than 60% of users prefer the digital experience to make their purchase, rather than visiting a car dealership. Consumers base their choice on real-time customer service, payment terms and speed, and all-round support, opting for a different brand if their needs are not sufficiently met. The brand itself is now subordinate to the "smart device" on wheels that will constantly improve the driving experience, allowing consumers to work, socialize and have fun in total safety and with full virtual assistance, constantly interconnected with the world around them (McKinsey, 2021).

The consumer's final choice will fall on the best "ecosystem of services" that meets their requirements and best fits the personalized demands of each customer.
Through the application of Artificial Intelligence cars will become Smart; in fact, the implementation of digital technologies will offer the consumer the possibility to travel in a vehicle that collects and shares data to inform him about road conditions and fuel consumption minimization, as well as being able to assist the user in driving, assisting him in driving (ADAS) and informing him about predictive maintenance interventions. ADAS stands for Advanced Driver Assistance Systems. ADAS are electronic systems that support the driver of a vehicle in a variety of situations from normal driving to moments of danger or emergency.
On the other hand, OEMs and car dealers will be able to offer in an increasingly competitive market, given the entry of new digital competitors, a more distinctive offer, enriching their product with a personalized customer experience for end users.
These changes are leading automotive companies to revolutionize their business models and to a strategic rethinking for the appearance of Start-Up and top players of the Tech and Energy world in the car market, at the same time they are contributing to a much broader social and ecological project, for which it is estimated that by 2030 the world we live in will be cleaner (Deloitte, 2022).

2.3.3 AI Supply – Chain Revolution

This new scenario will involve all the players in the automotive supply chain, i.e., OEMs, dealers and suppliers.
The implementation of Artificial Intelligence for OEMs will be reflected in four key elements:
New operating and business models: The higher levels of flexibility and customization demanded by the market require the adoption of new operating models and the development of new skills in data management for the customer base (i.e., exploitation of big-data and information from the customer journey; maintenance of brand-loyalty, after-sales services; creation of front-end platforms that allow users to configure, customize and order the car that best suits their needs). For this reason, OEMs are working closely with their dealership networks, both to integrate digital information systems and real-time customer data, and to ensure that sales structures are constantly

updated on technological innovations and vehicle customization possibilities. Consequently, this has required a review of supply-chain processes, with a view to ensuring the efficient, flexible, and timely delivery of customized services and specific product configurations.

Go-to-market strategies: The interest of a significant share of consumers in digital channels translates into new business opportunities for OEMs, such as the possibility to shorten the value-chain through B2C models and direct-to-consumer commercial strategies. Greater disintermediation in the sales process enables new sources of revenue and higher profit margins, thanks to the reduction of downstream levels in the distribution chain and the possibility of reaching end customers directly. However, all this requires a deep rethinking of commercial strategies and the acquisition of advanced skills (i.e., CRM management, creation of e-commerce platforms and "virtual showrooms", integration of "big-data / real-time analytics" systems, control and integration of digital channels, exploitation of data from digital touchpoints).

This will optimize the entire customer journey, improving both the purchasing experience and after-sales services for customers. In this way, OEMs will reshape their market strategy from "selling vehicles" to offering a high value-added "ecosystem of services" (Hofmann, 2021).

Technological enablers: Looking to the future, the distinctive value of vehicles will be increasingly focused on software components as opposed to hardware components, i.e., on digital functionalities and, in short, on "everything users will be enabled to do" in their cars, through a progressive integration between the physical and virtual worlds. This does not mean that hardware components will become irrelevant: on the contrary, vehicles will have to be rethought and designed with the aim of achieving a design capable of optimizing the user experience of passengers on board and fully exploiting the potential offered by new digital technologies.

OEMs will therefore have to continuously invest in the most innovative technological solutions to exploit new profit opportunities and maintain a distinctive position in the market.

Customer-driven approach: Finally, it will be essential to adopt a strategic approach that puts consumer expectations at the center of the value chain. OEMs will have to exploit and enhance the "information loops" coming from all interactions with the customer base (i.e., e-commerce platforms, apps, social media, partner sites, virtual showrooms), as well as from the increasing amount of data collected through new in-vehicle connectivity features. The objective will be to constantly update and improve specific aspects, performance and quality standards throughout the entire lifecycle of vehicles, in order to proactively adapt them to the new needs expressed by the market. The optimization of the "car product" also makes it possible to monetize the data and information sources coming from customers, thanks to the adoption of sophisticated "customer-driven" models oriented to maximize economic returns and focus business strategies on the elements with greater added value in the perception of consumers.

Against the backdrop of the technologies previously described and implemented by automotive industry players, the new supply chain will see close cooperation at the international level between OEMs, dealers, and suppliers in order to develop a more collaborative and cooperative approach in their interactions.

B2B strategies allow for greater integration both upstream and downstream in the value chain, thereby increasing the ability and timeliness to respond with appropriate responses to an increasingly complex, dynamic, and unpredictable market.

By working closely together, OEMs, dealers and suppliers strengthen mutual trust and transparency of transactions between global locations and joint ventures, resulting in a strategic approach to rebalancing the dynamics of production and sales (Neukart, 2021).

With the implementation of artificial intelligence, the automotive supply chain can be summarized through the following subprocesses:

Development: since the implementation of Artificial Intelligence, car design has become an almost fully automated stage of the production process. Technology makes available CAD models and simulations that enable a satisfactory degree of optimization of the resources used. The optimization is multidisciplinary, that is, it takes place on multiple sources, in terms of human resources, timing and cost. Data Mining allows obtaining a nonlinear regression model that describes the combination of inputs and simulates the final product. Besides, Data Mining is particularly important because it allows old simulation methods to be replaced with new ones that enable faster execution of adjustment processes.

Procurement: the procurement process is based on the prior analysis of a large amount of data, relating to suppliers, discounting, delivery reliability, and material and resource specifications. Data Mining allows the data to be processed and transformed into valuable information for the identification of certain supplier characteristics that reflect the required performance criteria.

The resulting optimization positively impacts the company's financial operations, as the data generated by the models contain the information on the key success factors. By means of predictive analysis, forecasts for the following weeks and parameters of greater influence are generated to make timely choices without risk (Back, 2020).

Logistics: in the automotive industry about logistics, four different steps can be distinguished: procurement logistics, production logistics, distribution logistics, and replacement pricing. The former, includes the purchase of raw materials and their transfer to the warehouse. In this step, AI enables through Data Mining to make predictions on prices and delivery reliability, as well as to optimize cost factors related to shipments.

In production logistics, which concerns the monitoring of internal processes i.e., handling and warehousing, AI makes it possible to optimize inventory levels and minimize timing.

Transportation of finished goods to customers or OEMs constitutes distribution logistics, in which AI enables processing information regarding all subcomponents of the modal supply chain. Data tracking includes from shipping to trucking.

In foreign exchange pricing logistics, AI and data mining enable the reduction of storage costs by providing timely analyses regarding the inventories of spare parts that need to be kept in stock according to age and model.

Analyses show that, especially in the field of logistics, forecasts made are of paramount importance in ensuring the continuity and efficiency of production. In the automotive chain, in fact, suppliers are a critical point, as a failure to deliver could slow down the entire system.

Data Mining enables data processing and provides an overview of all possible scenarios, both positive and negative, that could involve suppliers and cause production interruption.

Production: production gains benefit from the implementation of data mining. Constant storage and updating of parameters are critical to reduce the incidence of defects and achieve improvements in cost and resources used. AI can process data for both offline and online applications. In the former case, analyses focus on identifying problems and solving them, tying influence variables to objectives. For online applications, AI is implemented along with sub-steps performed manually by experts.

In the case of online applications, the process is fully automated and allows modeling of the integrated data to adapt the best choices aimed at optimizing the process.

Potential applications range from supply technology, to bodies, transmissions, and assembly and allow all subphases of the process to be adapted into one large system.
Marketing: in the field of marketing, Data Mining enables investigation especially of the relationship between customer churn and customer loyalty. In a mature market such as the automotive market, the main concern for auto companies is to prevent the loss of custom, that is, to maintain and cultivate customer loyalty. To maintain it, it is necessary to have the most complete information about the customer. Individualized information includes the customer segment to which he belongs, satisfaction, his post-purchase experience, product liking index, and possible competitors. Based on the collection of this data and its processing, AI can formulate optimal countermeasures, such as customized discounts and bonuses, to maintain and increase consumer satisfaction (Back, 2020).
Sales, after-sales and retail: in this specific case, the application of AI brought to the analysis of objective data is not sufficient and should be expanded to include subjective data relevant to the customer. Sales - data, identified discounts and retailer campaigns, are not sufficient to achieve timely analysis. Subjective data concern consumer preferences, obtained through surveys or third-party market studies, regarding brand, breakage rates and company loyalty. Therefore, AI combines objective and subjective sales data with marketing data, the phases of which are closely related. An analysis of these two phases enables optimization of market activities in terms of cost-effectiveness.
Connected customer: the customer has completely changed his relationship with the automobile from a mere product to a real service with which he is fully integrated. This effect is achieved through new information technologies and real-time data sharing. This effect is related to marketing and after-sales, providing the customer with personalized interfaces and real-time information (Hofmann, 2021).

2.4 Correlation between AI and Corporate Financial Performance and Corporate Social Responsibility

According to the World Economic Forum's Davos 2020 Manifesto, "the purpose of a company is to engage all its stakeholders in the creation of shared and sustained value. In creating such value, a company serves not only its shareholders, but all its stakeholders: employees, customers, suppliers, local communities and society at large." In accordance with this, the company pursues triple bottom-line goals, known as the 3 P's, people, profit and planet (Slaper & Hall, 2011).

In a highly dynamic and ever-changing environment, technology has become the key to development and survival. Investment in R&D has long been recognized as the driver of progress, through which companies can improve the quality of their products and the efficiency of supply chains (Salim & Bloch, 2009).

The investigation of the impact of R&D investment is a topic extensively analyzed in the academic literature and in the business environment, especially in the last two decades. Analyses conducted have amply demonstrated how technologies discovered and implemented return future monetary benefits, increasing firm value and market values (Chan, 2001; Eberhart, 2004). In addition, firms, through the implementation of new technologies, can maximize their profits and reduce costs significantly. Scholars argue that technological innovations are able to increase firms' competitiveness in the market and specialize in new business areas. (Gunday, 2011).

Research and development costs and innovation efforts fall under the category of intangible assets, i.e., those assets that as of today do not have a concrete manifestation, but in the medium to long term will generate benefits for society.

Research and development costs and innovation efforts fall under the category of intangible assets, that is, those assets that as of today do not have a concrete manifestation, but in the medium to long term will generate benefits for society. Over time, empirical studies have shown that R&D investment is the competitive weapon for obtaining the benefits identified by Intellectual Property. The benefits obtained would enable companies to implement new product and system technologies, lowering prices and using more cutting-edge elements and technologies. Overall, firms improve strategic and financial performance, increasing possible future earnings in line with other capital owned. (Rivette & Klein, 2008).

Modern literature shows how research and development efforts are positively correlated with firm performance and financial performance of firms (Salim & Bloch, 2009).

New technologies implemented have a statically positive effect throughout the work chain, going on to improve the product, organization, and customer relationships. This positive effect has been amply demonstrated in the automotive industry through studies (Atalay, 2013).

At the same time, attention over the years has focused not only on the financial consequences of implementing new technologies, but also on the corporate social responsibility (CSR) aspect. Companies themselves have changed their approach, not only pursued strategic and profitable ends, but aimed to achieve the satisfaction of their employees, consumers, suppliers, and remaining stakeholders. In addition, over the past two decades, the issue on environmental protection, a topic highly felt by businesses, has also taken over. Hence, companies are engaging in environmental compliance, using new technologies to reduce the effects and impact less on the surrounding environment.

Given the multitude of stakeholders involved, companies must leverage their technological capabilities and innovation capacity to meet social and environmental interests. Through this implementation, companies can reduce resource waste and lighten the environmental burden (Santana, 2015).

In the current scenario, especially in the field of engineering, scholars have investigated the potential of Artificial Intelligence (AI) to improve business performance, corporate and social relations, and enhance environmental sustainability.

The implementation of AI impacts corporate social responsibility from three perspectives: environmental, social and at the governmental level.

At the corporate governance level, companies can implement AI and benefit a range of stakeholders, both internal and external to the company. The application of AI affects a variety of public issues, including social justice, international security and economic vitality (Frey, 2017).

In companies, boards are increasingly adopting a data-driven approach to decision-making. According to Mark van Rijmenam (2018), "Artificial intelligence can help streamline decision-making processes, transform big decisions from visceral feelings to data-driven knowledge, and better predict the future outcome of those decisions. "

The big advantage is AI's ability to collect and process data, simplifying the decision-making processes through which corporate governance makes strategic and operational decisions. AI does not replace the workforce, but rather increases the ability to implement intelligent decisions. Data analytics integrated with AI enables corporate governance to make choices to optimize capital allocation, investment guidelines, and mitigate the risk of future losses (McKinsey, 2020).

At the environmental level, several theories demonstrate the positive effects correlating AI and environmental protection. In fact, studies define several derivative benefits. The first is the static environmental benefit arising from the product design and creation process, i.e., resources and C02 emissions. The second is the autonomous environmental benefit, which corresponds to the benefit obtained from the autonomous interactions between the AI-enhanced product and the external environment, in the post-purchase phase (Connelly, 2011; Spence, 2002).

Finally, from a social perspective, AI improves marketing and communication, customer interactions and sales, as well as the entire supply chain management. The goal of a company is to satisfy all parties having a relationship with the company, that is, all stakeholders.

Specifically, shareholder value corresponds to the return on investment based on the ratio of costs to revenues (Bender & Ward, 2008), for the customer it is the value associated with the product compared to alternatives in the market (Mahajan, 2016), for the employee it corresponds to the level of satisfaction in the work environment (Goswami, 2015), and finally for suppliers value creation consists of collaboration and the creation of derived added value (Moller & Torronen, 2003).

Implementing AI within the business system enables value creation for each of these stakeholders. AI allows shareholders greater completeness and processing of data to improve investment choice and reduce investment risk, translating into greater economic returns. For the customer, the value created by AI is evidenced in increased security in transactions, to an improvement in the experience and assistance during purchase and an increase in services that can be used post-purchase. For employees, AI enables them to optimize their productivity by using tools equipped with the intelligent knowledge. Finally, for suppliers, AI opens the door to the sharing economy, whereby suppliers are no longer considered merely sources of resources, but rather interact in a platform system and actively participate in the value creation process with the business and the customer (Kenney & Zysman, 2016).

Overall, advances resulting from AI implementation are disruptive and effective, creating value for all parties involved in the economic system (Kumar, Lahiri, & Dogan, 2018).

2.5 Correlation between AI and Companies' Merged Strategy

Covid-19 triggered an unprecedented disruption in global supply chains, bringing all areas of weakness in them to the surface and back up. The magnitude of the crisis affected every nation and industry, leading each to overhaul its business model and supply-chain to adapt to the sudden changes and restore the balance between supply and demand.

By disrupting supply chains, the pandemic has affected customers' ability to pay for their goods and services, rising production costs, increased receivables from companies, and the inability of companies to meet demand (PYMTS, 2020).

Scholars have noted how, over the years and especially in the wake of Covid-19, firms have exploited strategic inter-firm relationships to survive in such an uncertain and dynamic environment (Colombo, Piva, Quas, & Lamastra, 2020).

The goals for establishing strategic alliances consist mainly of the intent of inter-organizational sharing, access to technology to promote innovation, and lowering the costs of innovation (Leischnig, Geigenmueller & Lohmann, 2014; Rothaermel & Deeds, 2006).

In these terms, Alliance Management Capability (AMC) represents a source of competitive advantage (Dyer & Singh, 1998; Schreiner, Kale, & Corsten, 2009; Sluyts, Matthyssens, Martens, & Streukens, 2011; Schilke, 2014).

In compliance with the students, the term Environmental Dynamism (ED) is used to refer to a volatile and uncertain environment that poses significant changes in industry structures for companies to adopt due to new merging needs (Schilke 2014). During Covid-19, the choices made by governments to contain the spread of the virus had consequences for consumer behavior and choices (Sheth, 2020).

It is argued that in such surrounding, when the environment is turbulent and companies face new challenges, that change can have a positive impact on the dynamic capabilities of organizations.

Following the arguments, it is highlighted that environmental dynamism is crucial and influences the possibilities for change. Specifically, when ED is high, companies leverage their dynamic capabilities, the resulting benefits of which have a positive impact on performance. In contrast, when ED is low, dynamic capabilities are not utilized and enhanced by companies (Schilke, 2014).

In the current scenario, it has been observed that most automotive companies have implemented strategic alliances with other partners, aware of the key role played by AMC.

Alliance Management Capability is defined as the ability of a company to voluntarily change its own resource base to share and augment it with those of alliance partners (Helfat, 2007).

The literature illustrates several theories supporting the possibilities provided by AMC to improve organizational performance. It is believed that in the B2B context, proper alliance management can support routines for various tasks related to inter-enterprise relations. Against this, information exchange, resource mobilization and allocation, and sharing of logistical facilities can be used for multiple projects (Schilke, 2014).

To date, companies are implementing technology to achieve desired levels of organizational performance, and it is becoming necessary for companies to develop analytical capabilities. These capabilities are necessary because the volume of data collected must be decoded and translated into useful standardizations to exploit and maintain competitive advantage (Agarwal & Dhar, 2014; Fisher, DeLine & Czerwinski, 2012).

Thanks to the proliferation of Artificial Intelligence, we have reached a new stage, a sign of evolutionary progress, whereby the acquisition, storage, transfer, and sharing of data enables companies and managers to make the most profitable supply chain decisions based on processed and deciphered data (Cortez & Johnston, 2020; He, Zhang, & Li, 2021).

However, the usefulness of information derives primarily from its quality and the underlying processing and decision-making process. Scholars argue that in highly changing environments and unstable contexts, i.e., during a crisis, information sharing and transparency among partners is critical to responding to external changes and restoring equilibrium (Prasad, Zakaria & Altay, 2018).

Thus, we see the positive correlation between AI implementation and AMC; the establishment of strategic alliances, aimed at sharing resources and assets to decode the mass of data leads companies to adopt the best business and supply-chain choices (Kamaldin, 2020).

In addition, digitization in general is seen as the key source for the creation of new value opportunities, leading companies to abandon the traditional product-oriented model and adopt a service-oriented one (Kamaldin, 2020).

The benefits and outcomes, achieved by maximizing the use of technologies through the establishment of strategic alliances, are reflected in operational and financial performance.

The literature argues in terms of operational performance, the benefit achieved by AMC and AI is measured in terms of goal achievement, identifying operational performance as the sum of the results achieved by all companies. Up-to-date and processed information enables the development of the best solutions at the enterprise level and on decision-making processes. In addition, Real-time Information enables supply chain managers to reduce NWC, improve product and stock rotation, and consumer services. In conclusion, from the above, the literature emphasizes and supports the positive correlation between AI and OP and FP (Ayinder, 2019).
To sum up, AMC and the strategic alliances adopted enable AI to be leveraged and leveraged, the overall benefits derived positively reflect on operational and financial performance.

2.6 Research Questions

The analysis in this paper aims to measure the effects of the implementation of Artificial Intelligence within the automotive sector. Specifically, the study aims to investigate how the implementation of Artificial Intelligence within the automotive industry has affected key corporate performance variables and companies' merged strategy.

The initial question that my analysis aims to answer is whether, in the automotive industry, there is a relationship between the implementation of Artificial Intelligence and Corporate Performance.
Previous reports have shown the presence of this link even when studying dissimilar samples. Specifically, scholars argue that technological innovations are able to increase the competitiveness of companies in the market and specialize in new business areas. (Gunday, 2011). The implementation of Artificial Intelligence in the business system creates an enormous competitive advantage. it has been shown that companies that invest in AI achieve significant value if the new technology is applied at all business levels - they typically devote 10 per cent of their investments in AI to algorithms, 20 per cent to technologies and 70 per cent to integrating AI into business processes and agile ways of working (BCG, 2021).

AI enables companies to improve the production system by becoming more accountable, allows them to optimize the resources used, and consequently enables the company to grow more and increase its market value (Ullah, 2020).

H1: There is a significant positive relationship between AI implementation and Corporate Performance in the automotive sector.

The second research question of my analysis aims at analyzing the relationship between AI and Corporate Financial Performance. Previous studies have shown that AI enables optimization of the production process. Facilities and resources are optimally allocated, ensuring optimized planning aimed at limiting waste (Kohn, 2014). This enables companies to maximize profits and significantly reduce operating costs, ensuring greater profitability for the entire company (Gunday, 2011).
The implementation of AI enables the creation of value for all stakeholders involved in the business. Through AI, shareholders hold more complete information in order to reduce the risk of their investments and increase their economic return. For the customer, AI provides an improved shopping experience and payment security. through, AI, employees increase their productivity and suppliers become more engaged and active participants in the business value creation process (Kenney, 2016).

H2: There is a significant positive relationship between AI implementation and Corporate Financial Performance in the automotive sector.

The third research question is aimed at analyzing the relationship between AI and Corporate Social Responsibility by investigating the relationship with ESG factors.
The optimization of bread-making introduced by AI enables the reduction of energy consumption and the improvement of energy efficiency. It reduces the waste of resources and enables the recycling of resources (Tietenberg, 2018).
On a social and governance level, AI improves communication between business actors, ensuring a constant and fluid flow of information that improves the entire supply-chain organization, involving all levels of the company (Mahajan, 2016).

H3: There is a significant positive relationship between AI implementation and Corporate Social Responsibility in the automotive sector.

In addition, the analysis in this paper aims to investigate the relationship between AI and corporate strategy, i.e., to analyze how cost reduction for AI implementation is the basis of mergers between automotive industries.
Previous studies have shown that the main objective behind corporate merger strategies is the possibility of redistributing the costs associated with the implementation of new technologies (Kamaldin, 2020).
Data sharing has been shown to enable companies to make the most profitable supply-chain decisions (Zhang, & Li, 2021). In highly changing environments and in the face of an increasingly complex market, strategic alliances are an essential source to restore balance and meet market demands (Zakaria & Altay, 2018).
Sharing resources and strategic assets enable companies to decode more data and information, which is reflected in improved business choices (Kamaldin, 2020).

H4: There is a significant positive relationship between AI implementation Companies' Merged Strategy in the automotive sector.

3. Research Methods

The third chapter focuses exclusively on the method by which the research was conducted to prove the existence and hypothesized relationships. Firstly, the method used to collect and retrieve data is described, and secondly, the independent, dependent and control variables adopted in the regression equation are explained.
Finally, the models used to investigate the hypotheses mentioned are presented.

3.1 Sample and Data Collection Procedures

For the analysis of my study, I collected the necessary data directly from the Refinitiv Workspace database (formerly Thomson Reuters). Refinitiv Workspace is a platform for analyzing and collecting financial data, relating to common shares, market indices, stocks and bonds, exchange rates and macroeconomic data. This database also contains data from listed and unlisted companies, related balance sheet data and ESG data. It also provides access to portfolio analysis tools, M&A data and company composition and structure data.
For the first three research questions, aimed at investigating the impact of AI on company performance, I collected the first sample of data by extracting it directly from the section of the database that grouped companies by sector. The sector chosen was 'Automobiles & Auto Parts'.
The original sample had around 1000 automotive companies. Subsequently, the sample was skimmed based on the availability and retrievability of the data needed for my analysis. The final choice fell on a sample of 206 automotive companies. Data from last year, i.e., 2021, were taken into consideration.
For the fourth research question, aimed at investigating the incidence of AI in merger choices between automotive companies, I considered the largest automotive groups in the current industry scenario.
The chosen sample consists of 12 automotive groups as follows:
1) Volkswagen Group (Audi, Bentley, Bugatti, Cupra, Lamborghini, Porsche, Seat, Skoda and Volkswagen), 2) Toyota Group (Daihatsu, Lexus, Subaru and Toyota), 3) Renault Nissan Alliance (Alpine, Dacia, Datsun, Infiniti, Lada, Mitsubishi, Nissan, Renault), 4) Stellantis (Peugeot, Citroen, Opel, Fiat, Alfa Romeo, Lancia, Abarth,

Maserati, Chrysler, Jeep, Dodge, RAM), 5) General Motors (Baojuin, Buick, Cadillac, Chevrolet), 6) Hyundai Motor Group (Hyundai, Genesis, Kia), 7) Ford Group (Ford, Lincoln), 8) Honda Motor, 9) Daimler Mercedes (Mercedes-Benz, Smart), 10) BMW Group (BMW, Mini, Rolls-Royce), 11) Geely Volvo Group (Geely, Lotus, Volvo), 12) Tata Group (Tata, Jaguar, Land Rover).
The data collected are for the last 5 years, i.e., 2017 - 2021, in order to show how the importance of the incidence of AI in business decisions has increased over the years.

3.2 Variables and Measures

The description of the variables used for the analysis will follow the illustration and order of the proposed research questions.

3.2.1 Independent Variables

To test the hypothesis, my analysis revolves around a fundamental assumption. Since I cannot know the exact percentage that each automotive company has invested and spent on the implementation of Artificial Intelligence (not visible in Refinitiv Workspace), I used the dummy variable to represent it.
In the current scenario, Artificial Intelligence is implemented at all levels of the company and for this reason it is difficult to estimate its exact value.
The dummy variable is a numeric variable representing category data. Specifically, the dummy variable is a dichotomous quantitative variable, which can only take on two quantitative values. Typically, 1 represents the presence of a qualitative attribute and 0 its absence.
In the analysis, the presence of Artificial Intelligence is represented by 1 and its absence by 0, as following:

$$x_i = 1, presence\ of\ AI$$
$$x_i = 0, absence\ of\ AI$$

It was possible to attribute these values to the selected sample of companies thanks to the information contained in the company reports and market information of each company.

3.2.2 Dependent Variables

For the first research question, aimed at investigating the existence of the relationship between AI implementation and corporate performance, I considered Market Capitalization as the dependent variable.

Market Capitalization is considered the main universally accepted indicator of corporate valuation to express the aggregate value of a company. This indicator provides a clear picture of the company's market value, which is also influenced by new projects undertaken at company level. In particular, Market Capitalization is also influenced by the new technologies implemented and how these changes and increase the overall value of the entire corporate structure (Jaya & Sundar 2012).

$$Market\ Capitalization = Market\ Price\ per\ Share\ x\ Number\ of\ Outstanding\ Shares$$

For the second research question, aimed at investigating the relationship between AI implementation and company profitability, the dependent variables chosen are ROIC, ROE and ROA.

The Return on Invested Capital (ROIC) measures the return generated on invested capital. Four key components are considered in the calculation of ROIC, namely the use of operating income, tax adjustment, use of book values and time difference.
Operating income is necessary and preferable to net income because ROIC measures the return generated on all capital, i.e., debt and equity. The returns of both equity investors and lenders in the form of interest must be considered in the calculation. The

tax adjustment on earnings before debt is necessary to identify the after-tax value of capital.
The use of book values is necessary since the return is calculated on the invested capital, correctly expressed by the book values of debt and equity. Conversely, the market value is not suitable as it increases the value of existing assets, i.e., including earning potential. Finally, the invested capital must refer to the beginning of the period, i.e., the end of the previous financial year (Damodaran, 2007).

$$ROIC = \frac{Net\ Operating\ Profit\ After\ Taxes}{Capital\ Invested}$$

In contrast, Return on Equity (ROE) measures the return generated by the capital contributed by shareholders, i.e., the equity in the investment. ROE represents the earnings left for equity investors after repaying debt service costs. Consequently, only the book value of equity will be considered for the calculation and not also that of debt. The choice of the book value of equity must in any case refer to the beginning of the period (Damodaran, 2007).

$$ROE = \frac{Net\ Income}{Shareholders'Equity}$$

Return on Assets (ROA) measures the return generated by the total assets owned by a company. ROA is one of the most polar profitability indicators, used by Dupont in its proportionate triangle system, and considered the third most frequently used indicator (Mankin & Jewell, 2010).
This indicator is crucial for investors to determine how efficient the company is in using and utilizing its resources to generate profit. ROA combines the effects of profit margin and asset turnover, i.e., the ratio of Profit/Sales and Sales/Total Assets.

$$ROA = \frac{Net\ Income}{Total\ Assets}$$

For the third research question, aimed at investigating the relationship between AI implementation and CSR, i.e., social, governance and environmental responsibility, the independent dependent variables are the Renewable Energy Use ratio, Employee Satisfaction and Tobin's Q.

The Renewable Energy Use ratio is used as an indicator of environmental responsibility and provides a clear representation of companies' progress towards reducing energy consumption and environmental impact. Specifically, it indicates the ratio of renewable energy use to total energy consumption (IBM, 2020).
Il Renewable Energy Use Ratio rappresenta l'energia totale acquistata da fonti primarie di energia rinnovabile divisa per l'uso totale di energia e appartiene agli ESG Analytics (Refinitiv Workspace, 2021).

$$Renewable\ Energy\ Use\ ratio = \frac{Renewable\ Energy\ Sources}{Total\ Energy\ Sources}$$

Employee Satisfaction is a subjective measure that indicates an employee's degree of satisfaction with his or her job and the related work environment. These subjective assessments are influenced by compensation, workload, attitudes, work-life balance, staff relationships, working environment and company culture. The degree of satisfaction is an excellent indicator for assessing corporate social responsibility (Bhatti & Qureshi, 2007).
L' Employee Satisfaction represents the percentage of employee satisfaction reported by the company and includes the overall percentage of employees who are satisfied, and employees satisfaction index. It belongs to Social Workforce of ESG category (Refinitiv Workspace, 2021).

Tobin's Q is a good indicator of corporate governance, as it relates the market value of the company to the total assets held, showing how much the market values the company compared to its real book value.
The management of the company is, in fact, largely influenced by good governance and thus by the performance of the directors. In particular, proponents of the asset-based view believe that a balanced and diverse board of directors can positively influence the company's image and value in the market (Arosa, Iturralde & Naseda, 2010).

$$Tobin's\ Q = \frac{Total\ Market\ Value}{Total\ Assets}$$

For the fourth research question, aimed at investigating the relationship between AI implementation and strategic mergers between automotive companies, the dependent variable chosen is Total Assets.

Total Assets is considered a significant measure to represent firm size (Robinson, 2008). Consequently, according to the literature, strategic mergers between companies are aimed at distributing research and development costs. For these reasons, total assets are a useful indicator to illustrate how companies increase their assets and reduce their costs as a result of mergers (Ayinder, 2019).

3.2.3 Control Variables

The choice of control variables, i.e., those variables which are marginal in the analysis, but which may have an influence on the final regression outcomes, were chosen per research question.

For the first research question, the control variables chosen are: Ln Revenues, EV/EBITDA and EBITDA Margin.

Respectively, Ln Revenues is considered as it constitutes a good approximation of company growth and is a determining factor for company valuation. In support, the literature has pointed to the relationship between R&D investments and revenue growth (Hubbard, 1998). R&D investments are positively associated with cash-flow movements (Hall, 2002).

EV/EBITDA is a good approximation of the value of the company's stock price, and thus influences market capitalization accordingly. This measure is reliable because the firm's capital expenditures can vary substantially from period to period, and since the Enterprise Value represents the entire value before the firm pays off its debt, the EV/EBITDA multiple shows the smallest variation and dispersion across the industry (Berk & DeMarzo, 2017).

$$\frac{EV}{EBITDA} = \frac{Enterprise\ Value}{Earning\ Before\ Interest, Taxes, Depreciation\ \&\ Amortization}$$

The EBITDA Margin is a good indicator of corporate health, as it shows the company's ability or otherwise to properly utilize operating expenses and generate profits. The EBITDA Margin makes it possible to make assessments regarding the profitability of the running business, providing an indication of the efficiency of the company's operational structure (Berk & DeMarzo, 2017).

$$EBITDA\ Margin = \frac{EBITDA}{Revenues}$$

For the second research question, the control variables used are the Current Ratio, Asset Turnover and Financial Leverage.

The Current Ratio is a key financial liquidity indicator. It expresses the company's ability to meet its obligations in the short term, i.e., to repay current outgoings with current income. The Current Ratio is considered the cornerstone for assessing short-term corporate health (Berk & DeMarzo, 2017).

$$Current\ Ratio = \frac{Current\ Assets}{Current\ Liabilities}$$

Asset Turnover corresponds to the turnover ratio of total assets. It is a measure that indicates a company's efficiency in using its assets to produce sales. Specifically, it is an efficiency index, highlighting the company's ability to utilise its available resources (Berk & DeMarzo, 2017).

$$Asset\ Turnover = \frac{Total\ Revenues}{Total\ Assets}$$

Financial Leverage is expressed by the Debt to Capital Ratio and is an indicator to assess the financial structure of a company. It provides a clear representation of the company in terms of investment. The higher the indicator, the more the company is a risk to invest, as it means that the company is financed more by debt than by equity.
Interest-bearing debt, both short- and long-term liabilities are taken into account in the debt calculation (Berk & DeMarzo, 2017).

$$Debt\ to\ Capital\ Ratio = \frac{Debt}{Debt + Shareholders'Equity}$$

The third research question the control variables chosen are CO2 Total Emissions, Waste Recycled to Total Waste, Turnover of Employees, Net Employment Creation, Board Gender Diversity and Board Specific Skills.

The CO2 Total Emission variable represents the year-on-year percentage change in total CO2 emissions.

Waste Recycled to Total Waste is the ratio of total recycled and reused waste produced in tonnes divided by total waste produced in tonnes.
Both indicators belong to the ESG section, Environmental Emissions (Refinitiv Workspace, 2021)
The variable Employee turnover expresses the percentage of employee turnover within companies. This indicator includes employees who left the company voluntarily or involuntarily.
Net employment creation represents the growth of employment in the last year.
Both indicators belong to the ESG section, Social Workforce (Refinitiv Workspace, 2021).
Board Gender Diversity indicates the percentage of women on the Board of Directors.
Board Specific Skills represents the percentage of board members who have an industry-specific or strong financial background.
The indicators belong to the ESG section, Governance Management (Refinitiv Workspace, 2021).

For the fourth research question, the control variables adopted are Total Operating Costs, ROIC and EBITDA Margin.
Total Operating Costs includes all operating costs incurred by the company, ROIC is a good indicator for understanding the return on investment incurred, and EBITDA Margin is useful for understanding whether operating costs are eroding profits and are efficiently allocated and deployed.

3.3 Research Models

The research method used to prove the assumptions described above is Multiple Linear Regression.
MLR corresponds to an extension of ordinary least squares regression (OLS), which allows analysts to predict the value of one variable using information available on the other variable.
MLR involves a larger number of variables. It corresponds to a statistical technique by which the outcome of a (dependent) response variable can be predicted using several (independent) explanatory variables.

The statistical model is based on the following assumptions: i) the main assumption is that a linear relationship exists between the dependent variable and each of the independent variables, ii) the data must not show multicollinearity, i.e. high correlation between more than two explanatory variables, in accordance with the Gauss-Markov assumption.
The Multiple Linear Regression formula corresponds to:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \epsilon$$

where, $i = n$ and represents the number of observations; y_i is the dependent or predicted variable; x_1, x_2, x_{ip} represent the independent variables; β_0 is the y-intercept; β_1 and β_2 represent the regression coefficients and indicate the change in y relative to a one-unit change in x_{i1} and x_{i2}; β_p is the slope coefficient for each independent variable; ϵ is the random error or residual term resulting from the model.

In the analysis conducted for each research question, the regression method was applied in order to estimate the value of the dependent variable sought and its relationship with the other available independent variables.

Respectively, for the first research question - concerning the relationship between AI implementation and Corporate Performance - the corresponding formula results:

$$\begin{aligned} & Market\ Capitalization \\ & \quad = \beta_0 + \beta_1 * (Artificial\ Intelligence) + \beta_2 * (Ln\ Total\ Assets) \\ & \quad + \beta_3 * (Ln\ Revenues) + \beta_4 * \left(\frac{EV}{EBITDA}\right) + \beta_5 \\ & \quad * (EBITDA\ Margin) + \epsilon \end{aligned}$$

For the second research question - concerning the impact of AI implementation on Corporate Financial Performance - the corresponding formulas are:

$$ROA = \beta_0 + \beta_1 * (Artificial\ Intelligence) + \beta_2 * (Current\ Ratio) + \beta_3 * (Asset\ Turnover) + \beta_4 * (Financial\ Leverage) + \epsilon$$

$$ROE = \beta_0 + \beta_1 * (Artificial\ Intelligence) + \beta_2 * (Current\ Ratio) + \beta_3 * (Asset\ Turnover) + \beta_4 * (Financial\ Leverage) + \epsilon$$

$$ROIC = \beta_0 + \beta_1 * (Artificial\ Intelligence) + \beta_2 * (Current\ Ratio) + \beta_3 * (Asset\ Turnover) + \beta_4 * (Financial\ Leverage) + \epsilon$$

For the third research question - concerning the impact of AI implementation on corporate social responsibility and the environment - the corresponding formulas are:

$$Renewable\ Energy = \beta_0 + \beta_1 * (Artificial\ Intelligence) + \beta_2 * (C02\ Total\ Emissions) + \beta_3 * \left(\frac{Waste\ Recycled}{Total\ Waste}\right) + \beta_4 * (Turnover\ of\ Employee) + \beta_5 * (Net\ Employment\ Creation) + \beta_6 * (Board\ Gender\ Diversity) + \beta_7 * (Board\ Specific\ Skills) + \epsilon$$

$$Employee\ Satisfaction = \beta_0 + \beta_1 * (Artificial\ Intelligence) + \beta_2 * (C02\ Total\ Emissions) + \beta_3 * \left(\frac{Waste\ Recycled}{Total\ Waste}\right) + \beta_4 * (Turnover\ of\ Employee) + \beta_5 * (Net\ Employment\ Creation) + \beta_6 * (Board\ Gender\ Diversity) + \beta_7 * (Board\ Specific\ Skills) + \epsilon$$

$$Tobin's\ Q = \beta_0 + \beta_1 * (Artificial\ Intelligence) + \beta_2 * (C02\ Total\ Emissions) + \beta_3 * \left(\frac{Waste\ Recycled}{Total\ Waste}\right) + \beta_4 * (Turnover\ of\ Employee) + \beta_5 * (Net\ Employment\ Creation) + \beta_6 * (Board\ Gender\ Diversity) + \beta_7 * (Board\ Specific\ Skills) + \epsilon$$

The third hypothesis was also investigated individually at the Environmental, Social and Governance levels; the corresponding formulae are:

$$Renewable\ Energy = \beta_0 + \beta_1 * (Artificial\ Intelligence) + \beta_2 * (C02\ Total\ Emissions) + \beta_3 * \left(\frac{Waste\ Recycled}{Total\ Waste}\right) + \epsilon$$

$$Employee\ Satisfaction = \beta_0 + \beta_1 * (Artificial\ Intelligence) + \beta_2 * (Turnover\ of\ Employee) + \beta_3 * (Net\ Employment\ Creation) + \epsilon$$

$$Tobin's\ Q = \beta_0 + \beta_1 * (Artificial\ Intelligence) + \beta_2 * (Board\ Gender\ Diversity) + \beta_3 * (Board\ Specific\ Skills) + \epsilon$$

Finally, the fourth research question - aimed at analyzing the impact of AI implementation on the Companies' Merged Strategy - was investigated over a five-year period, and the corresponding formulas result:

$$Total\ Assets_{2017} = \beta_0 + \beta_1 * (Ln\ Artificial\ Intelligence_{2017}) + \beta_2 * (Ln\ Total\ Operating\ Costs_{2017}) + \beta_3 * (ROIC_{2017}) + \beta_4 * (EBITDA\ Margin_{2017}) + \epsilon$$

$$Total\ Assets_{2018} = \beta_0 + \beta_1 * (Ln\ Artificial\ Intelligence_{2018}) + \beta_2 * (Ln\ Total\ Operating\ Costs_{2018}) + \beta_3 * (ROIC_{2018}) + \beta_4 * (EBITDA\ Margin_{2018}) + \epsilon$$

$$Total\ Assets_{2019} = \beta_0 + \beta_1 * (Ln\ Artificial\ Intelligence_{2019}) + \beta_2 * (Ln\ Total\ Operating\ Costs_{2019}) + \beta_3 * (ROIC_{2019}) + \beta_4 * (EBITDA\ Margin_{2019}) + \epsilon$$

$$Total\ Assets_{2020} = \beta_0 + \beta_1 * (Ln\ Artificial\ Intelligence_{2020}) + \beta_2 * (Ln\ Total\ Operating\ Costs_{2020}) + \beta_3 * (ROIC_{2020}) + \beta_4 * (EBITDA\ Margin_{2020}) + \epsilon$$

$$Total\ Assets_{2021} = \beta_0 + \beta_1 * (Ln\ Artificial\ Intelligence_{2021}) + \beta_2 * (Ln\ Total\ Operating\ Costs_{2021}) + \beta_3 * (ROIC_{2021}) + \beta_4 * (EBITDA\ Margin_{2021}) + \epsilon$$

4. Results and Analysis

The following table shows the results obtained through empirical analysis in support of my research questions.

Table 6 shows Fisher's Table supporting the Analysis of Variance (ANOVA). From the multiple regression model, the resulting F-value corresponds to the ratio of sample mean to parametric mean. When the F-value exceeds the critical value, which can be found on Fisher's table according to the degrees of freedom identified by the model, the test is significant. This implies that the variables used make the averages vary significantly, thus rejecting the null hypothesis (H0), for which there is no relationship, and accentuating the hypothesis H1, for which the relationship is verified.

Table 7 shows descriptive statistics and sample distribution of the variables used.
Table 8 shows the correlation of the variables used for the analysis conducted. The tables show that there is no evidence of multicollinearity, i.e., the results obtained are significant as the variables used are not perfectly correlated with each other.
Table 9, Table 10 and *Table 11* show regression results Model 1, Model 2 and Model 3 respectively, corresponding to the research questions analyzed.
Table 11 is subdivided as follows: *Table 12, Table 13* and *Table 14* show regression results Model 3.1, Model 3.2 and Model 3.3 respectively, pertaining to Environment, Social and Governance.
Table 15 shows the regression results of Model 4, corresponding to the last research questions analyzed.

Table 6: Fisher's Table

Degree of freedom at the numerator

Degree of freedom at the denominator	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	20	24	30	40	60	100	200	+∞
1	161,45	199,50	215,71	224,58	230,16	233,99	236,77	238,88	240,54	241,88	242,98	243,90	244,69	245,36	245,95	248,02	249,05	250,10	251,14	252,20	253,04	253,68	254,31
2	18,51	19,00	19,16	19,25	19,30	19,33	19,35	19,37	19,38	19,40	19,40	19,41	19,42	19,42	19,43	19,45	19,45	19,46	19,47	19,48	19,49	19,49	19,50
3	10,13	9,55	9,28	9,12	9,01	8,94	8,89	8,85	8,81	8,79	8,76	8,74	8,73	8,71	8,70	8,66	8,64	8,62	8,59	8,57	8,55	8,54	8,53
4	7,71	6,94	6,59	6,39	6,26	6,16	6,09	6,04	6,00	5,96	5,94	5,91	5,89	5,87	5,86	5,80	5,77	5,75	5,72	5,69	5,66	5,65	5,63
5	6,61	5,79	5,41	5,19	5,05	4,95	4,88	4,82	4,77	4,74	4,70	4,68	4,66	4,64	4,62	4,56	4,53	4,50	4,46	4,43	4,41	4,39	4,37
6	5,99	5,14	4,76	4,53	4,39	4,28	4,21	4,15	4,10	4,06	4,03	4,00	3,98	3,96	3,94	3,87	3,84	3,81	3,77	3,74	3,71	3,69	3,67
7	5,59	4,74	4,35	4,12	3,97	3,87	3,79	3,73	3,68	3,64	3,60	3,57	3,55	3,53	3,51	3,44	3,41	3,38	3,34	3,30	3,27	3,25	3,23
8	5,32	4,46	4,07	3,84	3,69	3,58	3,50	3,44	3,39	3,35	3,31	3,28	3,26	3,24	3,22	3,15	3,12	3,08	3,04	3,01	2,97	2,95	2,93
9	5,12	4,26	3,86	3,63	3,48	3,37	3,29	3,23	3,18	3,14	3,10	3,07	3,05	3,03	3,01	2,94	2,90	2,86	2,83	2,79	2,76	2,73	2,71
10	4,96	4,10	3,71	3,48	3,33	3,22	3,14	3,07	3,02	2,98	2,94	2,91	2,89	2,86	2,85	2,77	2,74	2,70	2,66	2,62	2,59	2,56	2,54
11	4,84	3,98	3,59	3,36	3,20	3,09	3,01	2,95	2,90	2,85	2,82	2,79	2,76	2,74	2,72	2,65	2,61	2,57	2,53	2,49	2,46	2,43	2,40
12	4,75	3,89	3,49	3,26	3,11	3,00	2,91	2,85	2,80	2,75	2,72	2,69	2,66	2,64	2,62	2,54	2,51	2,47	2,43	2,38	2,35	2,32	2,30
13	4,67	3,81	3,41	3,18	3,03	2,92	2,83	2,77	2,71	2,67	2,63	2,60	2,58	2,55	2,53	2,46	2,42	2,38	2,34	2,30	2,26	2,23	2,21
14	4,60	3,74	3,34	3,11	2,96	2,85	2,76	2,70	2,65	2,60	2,57	2,53	2,51	2,48	2,46	2,39	2,35	2,31	2,27	2,22	2,19	2,16	2,13
15	4,54	3,68	3,29	3,06	2,90	2,79	2,71	2,64	2,59	2,54	2,51	2,48	2,45	2,42	2,40	2,33	2,29	2,25	2,20	2,16	2,12	2,10	2,07
20	4,35	3,49	3,10	2,87	2,71	2,60	2,51	2,45	2,39	2,35	2,31	2,28	2,25	2,22	2,20	2,12	2,08	2,04	1,99	1,95	1,91	1,88	1,84
24	4,26	3,40	3,01	2,78	2,62	2,51	2,42	2,36	2,30	2,25	2,22	2,18	2,15	2,13	2,11	2,03	1,98	1,94	1,89	1,84	1,80	1,77	1,73
30	4,17	3,32	2,92	2,69	2,53	2,42	2,33	2,27	2,21	2,16	2,13	2,09	2,06	2,04	2,01	1,93	1,89	1,84	1,79	1,74	1,70	1,66	1,62
40	4,08	3,23	2,84	2,61	2,45	2,34	2,25	2,18	2,12	2,08	2,04	2,00	1,97	1,95	1,92	1,84	1,79	1,74	1,69	1,64	1,59	1,55	1,51
60	4,00	3,15	2,76	2,53	2,37	2,25	2,17	2,10	2,04	1,99	1,95	1,92	1,89	1,86	1,84	1,75	1,70	1,65	1,59	1,53	1,48	1,44	1,39
100	3,94	3,09	2,70	2,46	2,31	2,19	2,10	2,03	1,97	1,93	1,89	1,85	1,82	1,79	1,77	1,68	1,63	1,57	1,52	1,45	1,39	1,34	1,28
200	3,89	3,04	2,65	2,42	2,26	2,14	2,06	1,98	1,93	1,88	1,84	1,80	1,77	1,74	1,72	1,62	1,57	1,52	1,46	1,39	1,32	1,26	1,19
+∞	3,84	3,00	2,61	2,37	2,21	2,10	2,01	1,94	1,88	1,83	1,79	1,75	1,72	1,69	1,67	1,57	1,52	1,46	1,39	1,32	1,24	1,17	1,01

Table 7: Descriptive statistics and sample distribution

	Mean	Median	Std Dev	Min	Max
Artificial Intelligence	0,66	1,00	0,48	0,00	1,00
Ln (Market Capitalization)	21,16	21,12	1,74	15,36	27,69
Ln (Total Assets)	21,18	20,87	1,76	15,84	26,57
Ln (Revenues)	20,81	20,57	1,80	16,27	25,73
EV/EBITDA	17,82	12,57	16,70	0,93	111,81
EBITDA Margin	0,13	0,12	0,08	0,01	0,43
ROA	6,84%	6,00%	5,00%	0,09%	30,53%
ROE	19,56%	15,19%	13,50%	4,07%	62,00%
ROIC	17,51%	13,38%	13,00%	3,00%	67,50%
Current Ratio	1,99	1,53	1,38	0,69	9,75
Asset Turnover	0,80	0,73	0,39	0,08	2,53
Financial Leverage	0,73	0,49	0,92	1,47	2,80
CO2 Total Emissions	-48,36	-44,00	0,21	-97,00	-14,39
Waste Recycled to Total Waste	0,52	0,49	0,21	0,10	0,99
Renewable Energy Use Ratio	5,59	3,24	13,00	-10,78	45,00
Turnover of Employees	18,18	14,12	15,18	1,66	57,00
Net Employment Creation	39,72	36,50	17,94	10,00	91,00
Employee Satisfaction	52,11	53,33	21,14	11,33	98,00
Board Gender Diversity	3,34	2,00	4,42	0,17	45,65
Board Specific Skills	44,15	39,00	20,78	10,00	98,00
Tobin's Q	0,46	0,40	0,22	0,10	0,99

Table 8: Pearson Correlation Matrix

		V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21
Artificial Intelligence	*V1*	1																				
Ln (Market Capitalization)	*V2*	0,38**	1																			
Ln (Total Assets)	*V3*	0,28**	0,81**	1																		
Ln (Revenues)	*V4*	0,31**	0,75**	0,96**	1																	
EV/EBITDA	*V5*	0,04	0,23**	-0,10	-0,16*	1																
EBITDA Margin	*V6*	-0,12	0,15*	-0,14*	-0,25**	-0,05	1															
ROA	*V7*	0,19**	-0,12	-0,32**	-0,30**	0,07	0,30**	1														
ROE	*V8*	0,19**	0,10	-0,17*	-0,14*	-0,06	0,16*	0,63**	1													
ROIC	*V9*	0,08	0,05	-0,20**	-0,17*	0,04	0,25**	0,52**	0,70**	1												
Current Ratio	*V10*	-0,03	-0,05	-0,30**	-0,35**	0,14*	0,44**	0,27**	0,11	0,30**	1											
Asset Turnover	*V11*	0,01	-0,15*	-0,10*	0,13*	-0,13	-0,38**	0,15*	0,19**	0,13*	-0,19**	1										
Financial Leverage	*V12*	0,01	0,04	0,25**	0,25**	-0,16*	-0,07	-0,22	-0,08	-0,14*	-0,29**	0,01	1									
CO2 Total Emissions	*V13*	0,17*	0,15*	0,27	0,23**	0,06	-0,16	-0,59**	-0,79**	-0,63**	-0,16*	-0,18**	0,14*	1								
Waste Recycled to Total Waste	*V14*	-0,16*	-0,18**	-0,31**	-0,28**	-0,05	0,18*	0,56**	0,79**	0,63**	0,18**	0,16*	-0,13*	-0,95**	1							
Renewable Energy Use Ratio	*V15*	0,17*	-0,14	-0,25**	-0,22**	-0,02	0,15**	0,64**	0,85**	0,67**	0,16*	0,18**	-0,14*	-0,94	0,90**	1						
Turnover of Employees	*V16*	0,00	0,20**	0,34**	0,36**	-0,26**	0,04	0,10	0,13	0,03	-0,14*	0,11	0,12	0,08**	-0,10	-0,03	1					
Net Employment Creation	*V17*	0,03	-0,14*	0,34**	-0,37**	0,22**	0,14*	0,04	0,06	0,17*	0,23**	-0,11	-0,13	-0,18**	0,23**	0,14*	-0,65**	1				
Employee Satisfaction	*V18*	0,04	-0,16*	0,38**	-0,41**	0,23**	0,13	0,06	0,05	0,16*	0,27**	-0,10	-0,14*	*-0,19**	0,22**	0,15*	-0,71**	0,87**	1			
Board Gender Diversity	*V19*	0,17*	0,18**	-0,13*	-0,10	0,31*	0,21**	0,28**	0,23**	0,17*	0,05	0,17*	-0,06	-0,21	0,19**	0,22**	-0,04	0,08	0,07	1		
Board Specific Skills	*V20*	-0,02	0,11	0,09	0,10	-0,01	-0,02	0,12	0,11	0,01	-0,09	0,09	-0,01	-0,12	0,10	0,13	-0,05	-0,02	-0,01	-0,01	1	
Tobin's Q	*V21*	0,17*	0,41**	0,02	0,02	0,55*	0,28**	0,17	0,13	0,17*	0,12	0,04	-0,05	-0,11	0,11	0,15*	-0,13	0,20**	0,19**	0,58**	0,04	1

With *,**,*** indicating significance at 10%, 5% and 1% confidence levels, respectively, based on two-tailed tests.

Regression Outcomes Tables

For research questions 1), 2) and 3), I considered 206 observations, representing 21% of the automotive market considered and reported by Refinitiv Workspace. The data are for 2021.
For research question 4), I considered a panel of 12 observations, major automobile groups, reported by Refinitiv Workspace. The data are for the time span 2017-2021.

Starting from Model 1 - which expresses the relationship between AI implementation and corporate performance in the automotive industry - I assumed Market Capitalization, a key parameter for corporate valuation, as the dependent variable. As independent variable R&D costs, and as control variables Total Assets, Revenues, EBITDA and EBITDA Margin.
Analyzing the coefficient of the independent variable, Artificial Intelligence, it turns out that p-value is $p<0.001$ for which the model is statistically significant and for which the null hypothesis is rejected, i.e., for which no relationship exists.
This is also confirmed by the Fisher value resulting from the model. F is higher than the critical value identified in Fisher's table based on the degrees of freedom reported by the regression (5 degrees at the numerator and 200 at the denominator), which is equal to 2.26. The resulting Fisher value of the regression model is equal to 308.74, and since $308.74 > 2.26$, the null hypothesis that there is no correlation between Artificial Intelligence and Market Capitalization is rejected.
Therefore, the hypothesis that there is a correlation between AI implementation and Firm Performance in the automotive industry is confirmed and the total fit of the model is significant. The existing relationship is positive with an Adjusted R Square of 0.88, a significance of 5,765E-92.
Analyzing the relationship between the control variables and Market Capitalization shows that this is positive for all variables considered, with a particularly significant level for Revenues and EV Margin.
In conclusion, Model 1 shows a positive relationship between AI implementation and Corporate Performance, measured by Market Capitalization.
The results are reported in *Table 9*.

Model 9 - Model 1: Corporate Performance

Indipendent Variables	*Ln (Market Capitalization)*
Intercept	1,01*
	(1,82)
Artificial Intelligence	0,52***
	(5,68)
Ln (Total Assets)	0,37***
	(3,75)
Ln (Revenues)	0,48***
	(4,67)
EV/EBITDA	0,03***
	(14,45)
EBITDA Margin	8,41***
	(13,49)
Observations	206
Adjusted R Square	0,88

With *,**,*** indicating significance at 10%, 5% and 1% confidence levels, respectively, based on two-tailed tests.

Model 2 shows the extent to which profitability is related to the implementation of artificial intelligence in the automotive industry. For this analysis, I assumed ROA, ROE and ROIC, key parameters for assessing Corporate Financial Performance, as dependent variables.

As independent variable Artificial Intelligence and as control variables Current Ratio, Asset Turnover and Financial Leverage.

The coefficients of the independent variable, Artificial Intelligence, is statistically significant, all reporting a p-value of $p<0.001$, and so the null hypothesis is rejected.

The Model identifies a critical value in Fisher's table of 2.42, based on the reported degrees of freedom (4 degrees at the numerator and 201 at the denominator).

Respectively, Fisher's values correspond to 79.02 for ROA, 140.95 for ROE and 88.93 for ROIC. All three are found to be greater than 2.42, and for these reasons the non-significance of the null hypothesis is confirmed.

Therefore, the hypothesis that there is correlation between AI implementation and Corporate Financial Performance in the automotive industry is accepted. The total model fit is significant. The existing relationship is positive with an Adjusted R Square of 0.61 for ROA, 0.73 for ROE, and 0.63 for ROIC.

The respective significances correspond to 3.569E-40 for ROA, 3.539E-57 for ROE and finally 2.219E-43 for ROIC.

Analyzing the relationship between the dependent and control variables shows that ROA is positively correlated with Current Ratio and Asset Turnover, while it is negatively correlated with Financial Leverage. At the same time, also ROE reports the same correlations as ROA. Instead, ROIC is positively correlated with all control variables.

In conclusion, Model 2 demonstrates the positive relationship between AI implementation and Corporate Financial Performance, represented by ROA, ROE, and ROIC.

The results are reported in *Table 10*.

Table 10 - Model 2: Corporate Financial Performance

Indipendent Variables	*ROA*	*ROE*	*ROIC*
Intercept	0,03***	0,08***	0,06***
	(3,95)	(5,36)	(3,89)
Artificial Intelligence	0,07***	0,26***	0,29***
	15,62	22,74	16,77
Current Ratio	0,01*	0,01*	0,02**
	(1,00)	(1,60)	(2,82)
Asset Turnover	0,01**	0,02*	0,02*
	(1,67)	(1,56)	(1,17)
Financial Leverage	-0,03*	-0,01*	0,01*
	(-1,35)	(-0,52)	(0,09)
Observations	206	206	206
Adjusted R Square	0,61	0,73	0,63

With *,**,*** indicating significance at 10%, 5% and 1% confidence levels, respectively, based on two-tailed tests.

Looking at Model 3 - related to what extent is Corporate Social Responsibility related to the implementation of Artificial Intelligence in the automotive industry - I decided to analyze the relationship both at the Corporate Social Responsibility level considering all variables together, and the individual impact of AI at Environment, Social and Governance (ESG) levels.
For Environment, I chose Total Renewable Energy as the dependent variable and Artificial Intelligence as the independent variable. As control variables, I chose C02 Emissions Total and Waste Recycled to Total Waste.
For Social, I adopted Employees Satisfaction as the dependent variable and Artificial Intelligence as the independent variable. As control variables I considered the Turnover of Employees and Net Employment Creation.
Finally, for Governance, I considered Tobin's Q as the dependent variable and artificial Intelligence as the independent variable. The control variables correspond to Board Gender Diversity and Board Specific Skills.

Model 3 first highlights the impact of the dependent variable and all control variables on Corporate Social Responsibility, namely Total Renewable Energy, Employee Satisfaction and Tobin's Q.
The result of the conducted analysis shows that the independent variable, Artificial Intelligence, is statistically significant, with p-value equal to $p<0.001$.
Therefore, the null hypothesis is rejected. In support, all Fisher's values are greater than the critical value identified based on the degrees of freedom (7 degrees at numerator 198 at denominator) and equal to 2.06. Respectively, Fisher's values correspond to 293.35 for Total Renewable Energy, 113.58 for Employee Satisfaction and 30.54 for Tobin's Q.
The total fit of the model is significant, and the dependent variables show a positive relationship with the independent and control variables.
The respective Adjusted R Squares are equal to 0.90 for Total Renewable Energy, 0.86 for Employee Satisfaction, and 0.51 for Tobin's Q.

Next, the impact of Artificial Intelligence's is observed at Environment, Social and Governance levels.
The coefficients of the independent variable, Artificial Intelligence are positive at ESG levels considered, and the variable is found to be statistically significant with a p-value equal to $p<0.001$. Therefore, the null hypothesis is rejected. The intervening relationship between ESG and AI is positive at all levels as evidenced by the coefficients.
Models1 3.1, 3.2, 3.3 respectively show an Adjusted R Square equal to 0.90 for Environment level, 0.86 for Social level and finally 0.51 for Governance.
Regarding the control variables, it appears that Total Renewable Energy is negatively correlated with C02 Emissions Total, while is positively correlated with Waste Recycled to Total Waste. Employee Satisfaction is negatively correlated with Turnover of Employee and positively correlated with Net Employment Creation. Finally, Tobin's Q is positively correlated with all its control variables, Board Gender Diversity and Board Specific Skills.

In conclusion, Model 3 and its subdivisions into Models 3.1, 3.2 and 3.3 demonstrate the positive relationship between AI implementation and the and Social Responsibility at the corporate and environmental levels.

The results are reported in *Tables 11, 12, 13* and *14*.

Table 11 - Model 3: Corporate Social Responsibility

Indipendent Variables	*Renewable Energy Use Ratio*	*Employee Satisfaction*	*Tobin's Q*
Intercept	0,06**	32,53***	-1,61*
	(2,57)	(13,28)	(-1,54)
Artificial Intelligence	0,13***	19,23***	5,15***
	(7,84)	(10,69)	(7,61)
CO2 Total Emissions	-0,007***	-0,12	-0,01
	(-8,66)	(-1,36)	(-0,38)
Waste Recycled to Total Waste	0,18*	-6,38	-1,96
	(0,24)	(-0,71)	(-0,52)
Turnover of Employees	0,0005	-0,45***	0,004
	-0,93	(-7,31)	-0,16
Net Employment Creation	-0,0001	0,46***	0,03
	(-0,33)	-7,07	-1,58
Board Gender Diversity	0,0001	-0,04	0,08***
	(0,55)	(-1,25)	-5,60
Board Specific Skills	0,003	-0,01	0,008*
	-0,06	(-0,45)	-0,76
Observations	206	206	206
Adjusted R Square	0,90	0,86	0,51

With *,**,*** indicating significance at 10%, 5% and 1% confidence levels, respectively, based on two-tailed tests.

Table 12 - Model 3.1 Environment

Indipendent Variables	***Employee Satisfaction***
Intercept	0,07***
	(5,06)
Artificial Intelligence	0,13***
	(8,22)
CO2 Total Emissions	-0,007***
	(-8,89)
Waste Recycled to Total Waste	0,02*
	(0,03)
Observations	206
Adjusted R Square	0,90

With *,**,*** indicating significance at 10%, 5% and 1% confidence levels, respectively, based on two-tailed tests.

Table 13 - Model 3.2: Social

Indipendent Variables	***Employee Satisfaction***
Intercept	32,53***
	(22,31)
Artificial Intelligence	18,95***
	(10,53)
Turnover of Employees	-0,45***
	(-7,24)
Net Employment Creation	0,48***
	7,44
Observations	206
Adjusted R Square	0,86

With *,**,*** indicating significance at 10%, 5% and 1% confidence levels, respectively, based on two-tailed tests.

Table 14 - Model 3.3: Governance

Indipendent Variables	***Tobin's Q***
Intercept	-1,28*
	(-1,63)
Artificial Intelligence	5,36***
	(8,10)
Board Gender Diversity	0,08***
	(5,64)
Board Specific Skills	0,007*
	(0,68)
Observations	206
Adjusted R Square	0,51

With *,**,*** indicating significance at 10%, 5% and 1% confidence levels, respectively, based on two-tailed tests.

Model 4 focuses on the fourth research question, related to what extent is the AI implementation and the Companies' Merged Strategy in the automotive industries.
To support this analysis, I considered Total Assets, an indicative measure of firm size, as the dependent variable, and Artificial Intelligence as the independent variable. In addition, the control variables considered are Ln Total Operating Costs, ROIC and EBITDA Margin.
In the chosen time frame, 2017-2021, corporate mergers between automotive companies have increased significantly to the present day.
The reason behind the choice of variables is due to the fact that according to the literature, as firm assets increase, consequent to mergers, operating costs are spread over more resources.

The analysis conducted shows a positive relationship with an Adjusted R Square gradually increasing from 2017 to 2021.

The values respectively correspond to 0.77 for 2017, 0.82 for 2018, 0.84 for 2019, 0.87 for 2020, and 0.88 for 2021.

The coefficient of the independent variable, Artificial Intelligence, is statistically significant with $p<0.05$.

Moreover, the Fisher values, identified by the regression model for each year, are greater than the critical value resulting from the combination of 4 degree of freedom in the numerator and 8 in the denominator. In fact, the critical value corresponds to 3.84 and the F values are 10.52 for 2017, 16.80 for 2018, 17.16 for 2019, 21.52 for 2020, and 23.14 for 2021.

Therefore, the null hypothesis for which there is no relationship is rejected.

The Model demonstrates the positive correlation between AI implementation and the strategic choices that lead automotive companies to merge into help group to share Artificial Intelligence costs.

The results are shown in *Table 15*.

Table 15 - Model 4: Companies' Merged Strategy

Indipendent Variables	Total Assets 2021	Total Assets 2020	Total Assets 2019	Total Assets 2018	Total Assets 2017
Intercept	14,98**	13,53**	-6,96*	-14,57	1,12
	(7,14)	(4,76)	(-1,14)	(2,04)	(0,15)
Artificial Intelligence	5,07***	2,11***	-0,05**	-2,29**	0,45**
	(4,94)	(2,69)	(-0,05)	(-2,61)	(0,35)
Ln (Total Operating Costs)	-0,21***	-0,05**	0,88**	0,72*	0,31*
	(1,70)	(-0,34)	(2,73)	(2,58)	(1,23)
ROIC	-0,36*	1,42	1,60	0,03**	0,33*
	-(1,52)	(-5,26)	-3,34	(0,36)	(1,26)
EBITDA Margin	0,11*	-0,63**	0,28**	1,49	0,35*
	(1,19)	-4,14	(1,31)	(4,55)	(0,83)
Observations	206	206	206	206	206
Adjusted R Square	0,88	0,87	0,84	0,82	0,77

With *,**,*** indicating significance at 10%, 5% and 1% confidence levels, respectively, based on two-tailed tests.

5. Discussion

This chapter presents the main conclusions reached through the statistical analysis conducted.

The following paper illustrated the implementation of Artificial Intelligence in the automotive industry, considering its economic, social, reputational, and environmental impact.

In a dynamic and increasingly competitive environment, stakeholders are increasingly interested in considering the companies they invest in not only in terms of remuneration, but also considering their environmental and social impact. The company is no longer just a production-oriented organization, but part of an increasingly broader and interconnected system. In this new system, companies must maintain a responsible attitude and adapt to current changes.

Artificial Intelligence is now the technology that ensures that companies maximize their profits, protect the environment, and create value for all stakeholders in the company's fortunes.

5.1 Conclusion Model 1: Relationship between Artificial Intelligence implementation and Corporate Performance in the automotive industry.

The first hypothesis concerns and confirms the positive relationship between AI implementation and Corporate Performance.

The analysis and results obtained are consistent with current literature, which argues that Artificial Intelligence enables companies to gain a competitive advantage and consolidate corporate position in an increasingly competitive and demanding market.

Through AI, companies are able to create value and enhance new areas of business. This is reflected in greater market value and growth as AI enables efficient resource allocation (Atalay, 2013).

5.2 Conclusion Model 2: Relationship between Artificial Intelligence implementation and Corporate Financial Performance in the automotive industry.

The second regression model illustrates the relationship between AI implementation and Corporate Financial Performance. The analysis demonstrates and confirms the positive relationship between the investigated variables, in compliance with the current literature.

The chosen dependent variables, ROA, ROE and ROIC, show a positive and significant relationship with Artificial Intelligence,

In fact, in accordance with the literature, AI implementation ensures efficient allocation of resources due to efficient forecasting models and allows monitoring the proper performance of investments. This is reflected in a higher return on assets and invested capital.

In addition, AI enables value creation for investors through systems that can monitor risk. This is reflected in a higher return on equity (Rivette e Klein, 2008).

AI is recognized as the engine of progress, through which companies can improve the quality of their products and the efficiency of supply chains (Santana, 2015).

5.3 Conclusion Model 3: Relationship between Artificial Intelligence implementation and Corporate Social Responsibility in the automotive industry.

The third regression model demonstrates the positive relationship between AI implementation and CSR, investigated at the environmental, social and governance (ESG) level.

In recent years, companies are becoming increasingly responsible and not only aimed at pursuing strategic ends. Companies strive to create value for all stakeholders and to respect and protect. the surrounding environment

In accordance with the literature, AI ensures the satisfaction of social and environmental interests through the exploitation of cutting-edge technologies and algorithms.

At the environmental level, AI enables the achievement of static benefit, i.e., minimization of CO2 emissions, and autonomous benefit, generated by the interaction between the high-tech product and the surrounding environment (Connelly, 2011; Spence, 2002).

At the societal level, AI has a positive effect on marketing and communication, applicable across the supply chain. AI creates value for all stakeholders, shareholders

(Bender & Ward, 2008), customers (Mahajan, 2016), employees (Goswami, 2015), and all suppliers (Moller & Torronen, 2003).

5.4 Conclusion Model 4: Relationship between Artificial Intelligence implementation and Companies' Merged Strategy in the automotive industry.

The fourth regression model illustrates the positive and significant relationship between AI implementation and merger strategies adopted by companies in the automotive industry.

The literature confirms how over the years companies have increasingly leveraged strategic inter-firm relationships to cope with an increasingly dynamic and complex environment (Colombo, Piva, Quas & Lamastra, 2020).

The only way to maintain a balance in this environment is to take advantage of new technologies and innovate. Inter-organizational sharing and cost allocation to promote innovation are the basis for strategic alliances and corporate mergers.

Scholars argue that in highly changeable environments, information sharing and transparency among partners are critical to respond to external changes and restore balance (Prasad, Zakaria & Altay, 2018).

For these reasons, AI emerges as the main reason behind strategic alliances to date, as it enables the acquisition, storage, transfer, and sharing of data, allowing managers to make more focused decisions (Cortez & Johnston, 2020; Lui, Zhang, & Li, 2021).

6. Managerial Implications

The results of the paper support the analyses that support the empirical confirmation of the positive association between Artificial Intelligence implementation and key corporate performance variables in the automotive industry.

Specifically, the positive relationship between AI implementation and Corporate Performance is confirmed in the literature (Chan, 2001; Eberhart, 2004; Salim & Bloch, 2009; 2014; Gunday, 2011; Kenney, 2016). In fact, the analysis shows that AI is positively correlated with market business value, i.e., Market Capitalization. It confirms the hypothesis that AI enhances value along the entire supply-chain, allowing the company to gain a stable competitive advantage in the long term.

Secondly, the positive relationship between AI implementation and Corporate Financial Performance is confirmed in the literature (Mishra & Pani, 2020; Mikalef, 2017; Benitez and Ray, 2012; Liu, 2020; Rout, 2018). AI enables companies to collect, collate and interpret a large amount of data to devise efficient business strategies. AI represents a weapon to challenge the new economic dynamics, allowing for optimizing resource allocation, weighting, and reducing the risk of investments and improving the automation and efficiency of business processes. The regression model demonstrates that AI has a greater influence on ROE and ROIC, i.e., it reflects a more weighted and timelier pattern of investments made. In agreement with the literature, the result shows how detailed data knowledge together with efficient algorithms can improve business performance in the revenue/cost ratio.

In addition, the positive relationship between AI and Corporate Social Responsibility is also widely confirmed and highlighted in the literature (Vinuesa, 2019; Sachs, 2019; Bocken, 2014; Lenssen, 2013). The key element in business is innovation, which must be reflected not only at the product level but at the business process level, ensuring sustainable solutions. Businesses are adopting a sustainable and responsible 'do more and better with less' approach. In this context, AI plays a key role, as it enables new technologies to improve efficiency and productivity. AI implemented within the business model enables companies to create value for society and to protect and preserve the environment.

The analysis conducted shows a significantly positive impact with the Renewable Energy Use Ratio, i.e., in terms of resources saved, and with Employee Satisfaction, by improving communication and information sharing in the workforce.

Finally, the literature also confirms the positive relationship between AI and Companies' Merged Startegy (Cortez & Johnston, 2020; He, Zhang, & Li, 2021; Prasad, Zakaria & Altay, 2018; Kamaldin, 2020; Ayinder, 2019). Indeed, the literature confirms that companies, to achieve the levels of efficiency required by the new competitive and ethical environment, need the processing and understanding of data. For these reasons, the implementation of AI becomes essential in the business environment. Companies through the sharing of resources and assets can first achieve benefits related to smart technologies, increasing their profits and redistributing costs related to its implementation. In fact, the study shows the inversely proportional relationship between operating costs and total assets. As groups and strategic alliances grow, costs tend to be increasingly minimized.

7. Study Limitations and Future Research

Although the empirical analysis in this thesis is extremely precise and accurate, we can identify some research constraints.

First, the first limitation concerns the choice of variable for representing Artificial Intelligence. Since I could not know exactly the amount of investment in AI incurred by each individual company, I chose to use the dummy variable. In Refinitiv Workspace, no data inherent in the implementation of Artificial Intelligence are available. For these reasons, the dummy variable makes it possible to assign and each company in the selected sample a value (0 or 1), indicative of the adoption or non-adoption of Artificial Intelligence, by consulting company reports.

Second, considering the experimental nature of the selected sample, it was necessary to convert some variables to their natural logarithm. This implies the possibility to investigate the positive or negative relationship between the independent variables, but it does not allow to express an open meaning of the influence of x variables on y variables.

Third, the possible limitation concerns the variables used.

In the first research question, the variable used to represent Corporate Performance corresponds to Market Capitalization, however, corporate value is a much broader concept and not only represented by market value.

In the second research question, the variables used to measure the impact on Corporate financial Performance are ROA, ROE, and ROIC. However, financial performance is not limited to the analysis of these three variables, but concerns indices of profitability, liquidity, leverage, efficiency and valuation.

For the third research question, the variables chosen are Renewable Energy Use Ratio, Employee Satisfaction, and Tobin's Q. Although these variables well define responsibility at the environmental, social and governance levels, they are not the only ones and corporate responsibility could be investigated on multiple levels.

Finally, for the fourth research question, the indicative variable to represent corporate mergers is Total Assets, indicative of firm size. This choice is due to the fact that accurate information regarding the specific sharing of assets and resources, as well as the distribution of costs, is not provided by company reports to properly identify how much the mergers significantly reduced the costs of implementing AI. Thus, my analysis assumes that as firm size, i.e., firm assets, increases, operating costs decrease. To make the study more comprehensive, one solution would be to perform the analysis by geographic areas, as my analysis considers a sample on a global scale, and therefore could contain limited generalizability to or each individual country or continent.

A possible analysis by geographic areas would allow for a more accurate analysis by country, considering the fact that not all countries in the world are at the same level in terms of Artificial Intelligence development and implementation.

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Table of Tables

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