Ca' Foscari University of Venice

Master's Degree programme

in

Economics, Finance and Sustainability

curriculum

Quantitative Finance and Risk Management

Final Thesis

# AI and Machine Learning in M&A

A Quantitative Analysis of Their Impact on Deal Outcomes

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**Academic Year**
2023 / 2024

## CONTENTS

**INTRODUCTION**

The introduction of AI and Machine Learning has transformed various industries, creating the opportunity to streamline complex processes and improve decision-making. In recent years, the integration of AI into the field of Mergers and Acquisitions, which are typically intricate transactions, demonstrated the potential to revolutionize each stage of the M&A process. This thesis explores the role of AI in M&A, evaluating its impact through empirical analysis with both real data and simulation techniques.

The first chapter provides a comprehensive overview of the features of AI and ML technologies, followed by an investigation of the M&A process. Then it focuses on how AI can be applied to each stage of M&A transactions, from the initial target identification to post-merger integration.

The second chapter presents an empirical analysis employing regression models applied to real-world data. Two Ordinary Least Squares (OLS) regressions are used to evaluate the impact of AI on deal outcomes, particularly focusing on time to completion and the overall cost-efficiency of transactions. However, the limited sample size of only 140 observations presents challenges in achieving statistical significance. Despite this limitation, the analysis provides valuable insights into the correlation between the Use of AI and M&A performance, showing the role of AI in optimizing transaction outcomes.

Given the limitations of the real-world dataset, the third chapter introduces Monte Carlo simulation to expand the dataset and strengthen the findings. This chapter explores the effect of AI on M&A under different hypothetical scenarios through the creation of a larger sample with “duplicated” data. The chapter evaluates how changes in AI implementation might influence other aspects of the M&A process, providing a comprehensive understanding of its impact.

The fourth chapter focuses on the ethical challenges that arise from the integration of AI into M&A. While AI presents clear advantages in terms of speed and efficiency, its adoption also raises concerns about transparency, data privacy and fairness. This chapter explores how companies can address these ethical dilemmas while leveraging AI for competitive advantage.

# CHAPTER I
# THE IMPACT OF AI AND ML IN THE BUSINESS WORLD

## Introduction

This chapter introduces the key concepts of AI and ML, highlighting their core features and showing their evolution to today's sophisticated algorithms. In the first section, we delve deeper into AI's characteristics and how its application in the business environment is rapidly growing. In particular, the finance sector has been profoundly marked by the introduction of the latest technologies in recent years and AI became an integral part of this business streamlining processes, improving efficiency, and managing risks in a data-intensive industry.

The second section shifts focus to the M&A industry, providing an overview of its role and significance in shaping corporate finance strategies. M&A activities play a vital role in driving growth, entering new markets, and fostering innovation across every industry. A general description of the M&A process is provided to explore the challenges and opportunities that companies face in executing deals efficiently.

The research's focus is explored in the third section, which present the intersection between AI and M&A to understand how these technologies are being increasingly employed throughout the various stages of the M&A process. AI's ability to analyze vast amounts of data and predict outcomes is reshaping traditional M&A practices, from deal sourcing to negotiation and integration. Moreover, it discusses AI's potential to enhance deal efficiency and decision-making across the lifecycle of M&A transactions.

The final section of this chapter highlights the crucial phase of due diligence, a key step in any M&A transaction, is presented. The role of AI in automating and improving the due diligence process is evidenced, as this is the first M&A stage with concrete evidence of how AI is improving the outcome of the deal, mitigating risks and streamlining document analysis, enhancing the accuracy and speed of evaluations.

## 1.1 Introduction to Artificial Intelligence and Machine Learning

### 1.1.1 Basic concepts on AI and ML

With today's technological advancement, AI and ML products have become fundamental as companies use them to process and analyse huge volumes of data, improve decision making and create accurate predictions. Artificial intelligence and machine learning represent a significant advancement in the field of computer science and can be utilized to improve every technology-enabled product or service, as well as industrial application. The terms of AI and ML are often used interchangeably when discussing predictive analytics, big data or other topics related to digital transformation, generating confusion. These are distinct technologies with different applications and domains, so what is the difference between ML and AI? AI refers to various types of technologies deployed in a system that enable it to have the capability to learn through complex reasoning and then act to solve a problem. AI refers to the automation of intellectual tasks which are typically the activities performed by humans. So, it is a broader concept that comprehend a range of techniques used to enable machines to perform tasks that require human intelligence. On the other hand, Machine Learning is a specific application of AI that allows machines to learn and improve based on experience and without being explicitly programmed. It is a subfield of AI and computer science and refers to a set of techniques used by computers to learn how to perform the tasks, using data and algorithms, to mimic the learning process of machines and increase the accuracy of systems without explicit instructions. Therefore, ML algorithms studies large amounts of data to identify patterns, learn from insights, and make informed decisions. For this reason, the performance of ML algorithms gradually improves over time as they are exposed to more and more data (the more data used, the better the model). So, while AI and ML are closely related, they are not the same thing, and understanding the difference between the two is crucial for leveraging their potential in various industries. Although AI is a science with multiple approaches that continues to advance as technology updates, advances in ML are creating change in virtually every field. In a rapidly evolving world, it is crucial to comprehend how AI and ML contribute to driving favourable business outcomes (Soori M., Arezoob B., Dastres R., 2023; Ashenden K., Bartosik A., Agapow P., 2021).

#### 1.1.1.1 AI features

AI is a branch of computer science whose purpose is to simulate human intelligence to solve problems. The main goal of AI is to develop an intelligent system that can perform complex tasks, by integrating technologies that mimic human decision-making processes, or even enhance them. The human behaviours that AI tries to replicate are simple everyday activities such as speech interpretation, object identification, prediction making and natural language generation. AI has a wide range of applications and can work with all types of data (structured, semi-structured, and unstructured data). AI systems employ logic and decision trees to learn, reason, and self-correct. For these reasons, it is increasingly becoming part of everyday life, as evidenced by the development of self-driving cars and the proliferation of generative AI tools. AI systems process huge amounts of data by simulating human capabilities, but usually humans supervise the learning process of an AI, being able to correct wrong decisions and support correct ones, but some new types of AI are designed to learn unsupervised, which leads to ethical dilemmas. The main quality of AI is that over time it improves its performance in making decisions with the automation of tasks to deal efficiently with problems. They can do this by using algorithms and data. Indeed, AI tools first collect an enormous amount of data, then applies mathematical models, or algorithms, that use the information to recognize patterns to make predictions in a process known as "training." When the algorithms have been trained, they are used in various applications, in which they continuously learn and adapt to new data. This makes AIs able to perform tasks such as data analysis, image recognition, language processing or other complex tasks with increasing efficiency and accuracy as time passes (Glover E., 2024; Martinez R., 2019).

There are several ways to classify AI, the simplest of which is to divide it into three main categories based on the way it learns: Artificial Narrow Intelligence, Artificial General Intelligence and Artificial Super Intelligence. The first one, (ANI) is an AI that specializes in one specific function or task. It excels in a narrow domain and operates in a limited context but has no ability to generalize its intelligence to other tasks. This tool complete very specific actions and it is used in various industries, applying ML to complete their specific tasks. This type is also referred to as weak AI, and some examples of it include

AI systems that can play chess, self-driving cars, product recommendation systems based on user preferences and image recognition software. Then, the second type of AI, (AGI), also known as strong AI, can perform and surpass a broad range of cognitive abilities like humans, like reasoning, abstract thinking, problem-solving and learning from experience. AGI perform tasks across different domains with a lot of versatility, and its capabilities could be built from supercomputers or technologies such as generative AI models (such as ChatGPT) and quantum hardware, although this is still a work in progress. The last type of AI, (ASI), is a theoretical AI that could potentially reach general intelligence level and learn at a fast rate that its capabilities become stronger than one of a human intelligence. ASI would have exceptional intellectual abilities such as scientific creativity and general wisdom beyond human capacity, reaching the stage of completely self-aware AI, fuelling media fear of “AI takeovers”, and in general, the development of ASI raises ethical concerns about its impact on society. (Strelkova, 2017; Betz S., 2024; Glover E., 2024)

Afterwards, four types of AI can be categorized based on functionality, that is, how an AI applies its learning capabilities to process data, interact with its surroundings and respond to stimuli. The first of four types of AI are reactive machines, systems with limited capacity that can respond only to immediate requests and tasks, without the capability to store memory, learn from past experiences or enhance their functionality through experiences. They are confined to responding to a specific set of inputs and unable to build upon previous knowledge or perform more complex tasks. Responsive machines are useful for completing basic autonomous functions, and some examples of how it is used nowadays are filtering spam from an e-mail inbox or suggesting products based on purchase history. However, they can’t rely on experience to implement the decision-making, and this makes reactive machines suitable for completing a limited number of duties (another famous example of this AI is Netflix's AI-powered recommendation engine that suggests movies based on a user's viewing history). The second category is known as limited memory AI, which can store past data and use it to make predictions, with limited, short-term knowledge. It is called “limited memory AI” and is based on deep learning, which simulates the function of neurons in the human brain and enables machines to absorb data from experiences and learn from them, thereby improving the accuracy of their actions over time. Presently, limited memory models make up the majority of AI applications and can be applied in a wide range of settings, including chatbots and virtual assistants, as well as more advanced applications such as self-driving cars. Essentially, this type of AI, looks to the past for clues to predict future outcomes. Limited memory AI can be created through continuous training of a model to analyse and utilize new data, or through the construction of an AI environment where models can be automatically trained and updated. Examples of it include ChatGPT, self-driving cars, chatbots and virtual assistants which simulate human conversation through deep learning. They learn from data and remember information about the user whenever they interact more with these systems, enabling them to provide personalized responses. Self-driving cars continuously gather and process environmental data as they move along the road, which helps them predict when to stop, turn or avoid an obstacle. Then there is "theory of mind", an idea of AI that is capable of recognizing and interpreting the emotions of others. This concept, which is borrowed from psychology, describes humans' ability to understand and predict the actions of others based on their emotional state. While theory of mind has not yet been fully realized, it is considered the next major step in AI development. It has significant potential benefits, but so are the potential risks. Since emotional signals are complex, AI machines would need to spend lots of time perfecting their ability to read them, which could lead to errors during the learning process. Furthermore, some people are concerned that once AI systems are able to interpret emotional signals, this could lead to the automation of certain jobs. But remind that this is still a theoretical type of AI that has not being created yet, although it is seen as a system that can perceive, comprehend and use human emotions to make predictions and decisions. To suggest how theory of mind application would revolutionize technology, there is a famous example of a self-driving car that performs better than a human driver because it won't make the same human errors, but this vehicle would not have the same human sensitivity and would be unprepared to situation for which has not been programmed, such as slowing down near where children are playing. Instead, equipped with theory of mind, the same car would anticipate and respond to potential hazards such as a child playing near a street. The last type is self-aware AI, an AI that possesses self-awareness. This concept involves the creation of machines that possess a sense of self-awareness and the capacity to comprehend the emotional state of others. The achievement of this is expected to result in machines that are beyond human control. Although self-aware AI does not currently exist, it is theorized to possess human consciousness and the capacity to understand its own existence in the world. (Betz S., 2024; Glover E., 2024)

#### 1.1.1.2 ML features

To create AI programs capable to analyse data and solve problems, computer programmers and software developers apply tools such as machine learning, neural networks, deep learning, computer vision, natural language processing (Artificial Intelligence vs. Machine Learning, 2024). To build an AI system the first step is through ML, a series of algorithms that analyse large datasets, learn from it by identifying patterns and make informed decisions based on those learned insights. ML algorithms utilize statistical models to learn and can self-correct when provided with new data to gradually improve a task, without having been programmed (for that specific task). ML relies on self-learning algorithms to produce predictive models and so it has a limited scope of applications than AI systems, so it can use only structured and semi-structured data. ML typically employs neural networks, which consist of a series of algorithms that process data by emulating the structure of the human brain. These networks contain layers of interconnected “neurons” that process information and transmit it to one another. They can make predictions, recognise complex patterns within the data and learn from their mistakes by adjusting the strength of the connections between these neurons. Neural networks are useful for understanding human speech, recognizing images and translating words between languages. Another crucial subset of ML is deep learning, which utilizes artificial neural networks that are composed of multiple hidden layers through which data is processed. This enables a machine to recognize increasingly complex patterns, making connections and weighting input for optimal results. Deep learning is especially effective at tasks such as image and speech recognition and natural language processing, making it a critical component in the development and advancement of AI systems. Another subset of ML is Natural Language Processing (NLP), a field of computer science that focuses on teaching machines to understand and generate human-like language. By combining concepts from linguistics, machine learning and deep learning, NPL enables computers to extract information from unstructured text or voice data. Some common applications of NLP include natural language generation, speech recognition, and virtual assistants, such as those found in smartphones and smart homes. While NLP can recognize and respond to voice commands, it is not capable of performing tasks beyond this scope. Finally, computer vision, another application of ML, involves teaching machines to analyse and understand visual media, such as images and videos. By using deep learning and convolutional neural networks to break down images into pixels and tag them accordingly, computers can distinguish between different shapes and patterns. This application of ML is used for a variety of tasks, including image recognition, classification and object detection. In addition, it is used in applications such as facial recognition and sensing in self-driving cars and robots (Glover E., 2024; How is AI different from ML, 2024; Rezaei N., Jabbari P., 2022).

Therefore, machine learning aims to create machines that can learn autonomously from data to increase output accuracy and perform specific tasks. The goal of ML models is to try to minimize the error between their predictions and the actual ground truth values. The next step to realize this, is define an error function (also called an objective function or a loss-function) because the objective of the model could be, for instance, predict the expected price of a stock in the near future or classify data into different categories. We can compare the model's prediction with the actual value and change the model's parameters so that the next time we repeat the operation, the error between these two values is smaller. The iterative process is repeated until the model inputs are accurate and the difference between the predictions and the true value is minimal. ML models are algorithms that minimize errors by making some assumptions and repeating them (Oppermann A., 2023).

ML has four different categories such as supervised and unsupervised learning, semi-supervised learning and the reinforcement learning (Oppermann A., 2023; Glover E., 2024). The first one requires a lot of human control; It can train models to complete tasks in classification, regression or forecasting and for this it's one of the most popular forms of ML. It is commonly used to detect inbox spam, create recommender systems, and predict stock and housing market values. The process of supervised learning involves dividing input and output data into distinct categories and fed continuously labelled data into ML models trained by human. Consequently, the accuracy of predictions improves with each new dataset. Additionally, human feedback is provided to the ML algorithm, helping it learn and enhance its performance over time. For instance, Gmail and other email clients automatically classify emails as spam or promotions, thereby hiding them from view. Another example is regression algorithms, which are applied to forecast trends by finding relationships between outcomes and other independent variables (the most used are linear regression algorithms but also logistic regressions, ridge and lasso regressions).

With unsupervised learning there is less work for humans as unlabelled data is processed by the system. This type of ML is used to discover patterns or anomalies in huge unstructured datasets that might not otherwise be found by humans. Its algorithms groups information based on similarities and differences, through the creation of relationships between data points; it is applied by computer vision, customer segmentation, and violation detection. Clustering algorithms are the most popular example of unsupervised machine learning, and these are used to notice similarities between raw data and group information accordingly. Thus, they are employed to provide structure to raw data and are useful with marketing data to gather information about customers and to detect fraud. Another type is dimensionality reduction, which is the process of reducing the number of features within a dataset while preserving important properties of the data. This is used to reduce complexity, processing time, storage space, and overfitting a ML model (Bowman A.D., Jololian L., 2023).

The third type is semi-supervised learning, which is a balanced mix of supervised and unsupervised. With this hybrid approach, small amounts of labelled data are processed alongside numerous blocks of raw data. This type of ML saves time, cost, and effort compared to supervised learning, and its algorithms are more efficient than unsupervised learning algorithms at identifying relevant patterns and making accurate predictions. Semi-supervised learning is used for text document classification, speech recognition, and fraud detection. Examples of this category are self-learning algorithms and label propagation algorithms.

The last type of ML are AI-based software programs equipped with sensors that respond to their surrounding environment making independently decisions to achieve the desired outcome. As the intelligent agents interacts with their environment, they learn how to achieve optimal competence, through trial and error and through positive reinforcement during the learning process. Reinforcement learning is used to help machines acquire skills and behaviours in robotics and self-driving cars. The most important algorithm of this type of ML is Deep Reinforcement Learning, that combines deep learning with reinforcement learning and is used in the development of video games, self-driving cars and robots. With deep reinforcement learning are required greater computing power and large amounts of data. (Biba J., 2023; J. Levy, Y. Lu, M. Montivero, O. Ramwala, 2023).

So, while AI stems from the idea of a machine being able to simulate human intelligence, machine learning does not. The latter aims to teach machines how to perform a specific task and deliver accurate results by identifying patterns. There are several advantages to using AI and ML together; they can offer significant benefits to organizations of all shapes and sizes, with new possibilities constantly growing. Especially, in modern businesses, with the increasing size and complexity of the amount of data, there is a growing need for automated and intelligent systems to help organize and automate activities to generate value to achieve ever better results. Some of the business benefits of using AI and ML are wider data ranges, analysing a much wider variety of unstructured and structured data sources and faster decision-making (AI vs ML: How Do They Differ, 2024). These concepts form the foundation of AI and ML technologies and are essential for understanding how machines can learn, reason, and make decisions based on data (J. Levy, Y. Lu, M. Montivero, O. Ramwala, 2023).

### 1.1.2 General applications of AI in the business environment

Artificial intelligence has a wide range of applications across different industries and is already helping to streamline business processes and increase their efficiency. AI and ML can lead to a variety of automated tasks, and since technology affects virtually every industry, companies are forced to integrate them into their business if they want to survive within a competitive market. Today, AI has already been implemented in smartphones with AI assistants, e-commerce platforms with recommendation systems, autonomous driving vehicles, fraud detection systems online and robots for dangerous jobs. (Oppermann A., 2023; Glover E., 2024)

The two main sectors in which the introduction of AI is bringing great changes are business and medical. In the business environment the first activity that has been transformed by new technologies is customer service. Here virtual assistants and AI-driven chatbots can provide personalized support, improve customer service efficiency and handle customer demand autonomously while reducing operational costs. In addition, AI has helped revolutionize predictive analytics and forecasting; AI algorithms can analyse data to predict trends, anticipate market changes and identify risks and opportunities, enabling companies to make data-driven decisions. The most significant development brought by AI in business activities is process automation and optimization. AI technologies streamline repetitive tasks and workflows, automate business processes, and enhance operational efficiency across a range of functions, including finance, HR, marketing, and supply chain management. Another area in which AI's analytical abilities provide great advantages is that of personalized marketing. In this case, AI can personalize marketing campaigns by analysing user data and preferences to recommend personalized products and offers, increasing customer engagement and driving sales. Furthermore, AI algorithms can help companies prevent fraud by detecting patterns of fraudulent activity in financial transactions.

The second sector particularly affected by artificial intelligence is the medical sector. In this context, AI has improved fundamental tools such as diagnostic imaging: artificial intelligence is able to analyse medical images such as X-rays, MRIs and CT scans to assist radiologists, simplify the detection of anomalies and make accurate diagnoses. It has also contributed to the discovery of new drugs, as artificial intelligence algorithms can identify potential drug candidates, predict drug interactions and therefore accelerate the discovery process. In this environment, AI can be useful to obtain personalized medicine. Thanks to the analysis of genetic data, AI allows you to personalize treatments for individual patients and predict disease risks. Finally, AI-based devices can monitor patients remotely, collect their health data and promptly report potential health problems to healthcare professionals. These applications demonstrate the versatility and impact of AI in transforming business operations and revolutionizing healthcare practices (J. Levy, Y. Lu, M. Montivero, O. Ramwala, 2023).

Another major innovation that could facilitate a significant portion of the automatic work in today's business environment is Generative Artificial Intelligence. Tools like AI chatbots, such as ChatGPT, Gemini, Grok and Claude, utilize AI to generate written content in various formats, ranging from essays to code and answers to simple questions. Generative AI enables businesses to innovate and create in unprecedented ways by leveraging advanced algorithms, allowing for the generation of novel and creative content such as images, text, video and audio. This creativity is particularly valuable in industries such as advertising, marketing, and content creation, where capturing audience attention and driving engagement is essential. To function, a generative AI model is trained on massive datasets, identifying patterns within them and subsequently generating outputs that resemble this training data. Generative AI has gained immense popularity in recent years, especially with the emergence of chatbots and image generators. These tools are commonly used in marketing, entertainment and other industries to speed up the creation of contents. Generative AI serves as a cornerstone of AI's impact on business environments, offering unparalleled capabilities in creativity, personalization, and efficiency. By incorporating Generative AI into their operations, businesses can unlock new opportunities for innovation, differentiation, and growth in an increasingly competitive marketplace. However, this technology also presents some challenge as they can be used to spread disinformation creating fake content and deepfakes. Additionally, AI-generated material could potentially infringe on people's copyright and intellectual property rights (Glover E., 2024).

### 1.1.3 AI in Finance and evolution phases of AI

Among several industries, finance emerges as a forerunner in the adoption of the latest technologies. As operations in finance require speed, heavy reliance on data and high accuracy, it becomes an industry particularly prone to embrace technological innovations that promise to greatly improve efficiency and increase competitiveness. This sector is particularly enhanced with the new frontiers of technology-from digital payments to blockchain, from financial data analytics systems to algorithmic trading platforms. The advancement of AI in finance demonstrates a trend towards greater sophistication and integration of AI technologies, which are increasingly recognized as essential for achieving a competitive edge in the financial industry. Machine Learning models are increasingly being used in various domains, such as finance and healthcare, to boost AI applications. This is largely due to their superior predictive accuracy compared to traditional statistical models (L'Intelligenza Artificiale nell'M&A, 2024; Cardarelli A., 2024).

Over the past two decades, the use of AI in finance has evolved significantly due to technological advances in a wide range of applications. The increasing number of publications and research studies shows the growing adoption of AI applications in various financial sectors. Some of the activities in which AI has been applied include big data analysis, predictive and forecasting systems, and detection systems such as fraud detection. AI in finance has become central to risk management (example in credit risk assessment), trading strategies and customer relationship management, portfolio management, and investor sentiment analysis. The evolution of AI comes from advances in machine learning, natural language processing, and data mining techniques, techniques that enable predictive analysis and more accurate trading strategies, leading to improved financial decision-making. Market stability is also improved through the implementation of AI tools by reducing volatility and information asymmetry. This allows for more profitable investment systems and accurate performance evaluations.

The first area where the introduction of AI and ML had a great impact is risk management, here they help assessing and managing various types of financial risks. The analysis of historical data that AI and ML models can provide lead to the identification of patterns that traditional methods might miss, improving the accuracy of predictions of bankruptcies, credit risk and defaults. Then, AI enables continuous assessment of risk factors on a real-time basis, allowing financial institutions to respond quickly to emerging risks. These technologies also lead to more efficient trading decisions; by analysing a large amount of data in real-time, they improve trading strategies. ML models can improve trading performance by optimizing trading strategies based on changing market conditions. AI also has qualities that go beyond human capabilities, such as the speed of its algorithms that improve market inefficiencies. Major applications of AI and ML involve predicting market trends, financial performance, stock prices, and economic indicators to help companies and investors make informed investment decisions through predictive models that are constantly updated with new data. These tools provide insights into market trends and economic indicators through the analysis of complex and even unstructured datasets, leading to better investment decisions. To date, ML algorithms are used to identify and prevent fraudulent activities through the analysis of transaction patterns and anomalies. ML algorithms, detect unusual patterns in transaction data to flag potentially fraudulent activities through the classification of firms based on their financial health with the goal of detecting unusual transactions with a warning system. AI systems can learn from new fraud patterns over time, reducing false positives and thus improving their detection capabilities. Personalized financial advice through portfolio management is also an AI prerogative, allowing investment strategies to be optimized based on individual client profiles, AI tools analyse market conditions and adjust asset allocations to maximize returns while controlling the risk. ML tools can automate portfolio adjustments based on client goals and market conditions, allocating resources optimally. AI technologies meet and follow regulations to improve security measures against cyber threats and reduce the risk of human error. Vulnerability analysis to identify potential security threats enables good fraud prevention by improving overall financial security. In addition, AI is also used in the field of text mining and sentiment analysis: it analyses news articles, social media and other textual data to assess market sentiment and provide insights for trading strategies. AI then identifies emerging trends and changes in market sentiment that can impact investment decisions. The sentiment analysis combined with natural language processing gauge market sentiment. Therefore, AI is also used for behavioural analysis through sentiment analysis, which allows to understand investor behaviour. These areas highlight the different applications of AI and ML in finance and their impact to improve operational efficiencies and decision making. (Weber P., Carl K. V.; Hinz O., 2024).

There are also some difficulties related to the use of ML in finance, one is that ML models often function as "black boxes," making it hard to understand the rationale behind their predictions. Despite their ability to achieve high levels of predictive performance, this black-box nature can be a problem in regulated industries. Regulatory authorities struggle to evaluate the risks associated with the use of AI methods, as they may not be able to validate these complex models. For instance, the use of AI in credit lending can lead to automated decisions that classify a company as being at risk of default, without providing an explanation for the underlying rationale. This lack of transparency can hinder trust. The recently proposed European regulation on AI, the AI Act (European Commission, 2020), aims to address these issues by introducing a set of integrated requirements. The AI Act takes a risk-based approach to AI applications and categorize them into four levels: unacceptable risk, high risk, limited risk, and minimal risk. The introduction of regulations, such as the European AI Act, requires that high-risk AI applications meet specific criteria, including sustainability, accuracy, fairness, and explainability. The ethical considerations about the use of AI are further discussed in Chapter Four, since the presence of anomalies can significantly impact the performance of ML models and there is the need to ensure robustness to maintain the reliability of predictions. ML models can amplify biases present in the training data, leading to unfair outcomes across different population groups. These challenges emphasize the need for integrated approaches that can enhance the trustworthiness and effectiveness of ML applications in finance (Giudici P., Raffinetti E., 2023; Bahoo S., Cucculelli M., Goga X., Mondolo J., 2024).

### 1.1.4 Specific examples of AI's impact on efficiency, innovation, and competitiveness

The use of AI and ML in business processes has become increasingly prevalent in many industries, resulting in improved efficiency, better customer experience and accuracy. AI is useful in the management of business mechanisms as it enables the automation of back-end activities and repetitive processes, enabling streamlined operations at every stage. This brings a key benefit: the reduction of human error. In processes involving the analysis of numerical or textual data, AI-based automations can process information without oversights precisely and accurately, unlike humans, who are prone to errors due to fatigue or mistakes. Another great benefit generated by AI-based automation is the increase in operational efficiency, thanks to the automation of most redundant activities and processes. The result, in addition to increased productivity along with time and cost savings for companies, is the empowerment of employees, who can finally focus on tasks with significant and higher-order responsibilities, leaving the automation of routine activities to AI tools. Corporate workers benefit twice: they not only reduce stress and burnout, but they can maximize their talent and potential in more complex tasks. AI also allows to personalize customer experiences at scale, thanks to personalized communication with each customer and this, even if the total volume increases, leads to customer satisfaction and loyalty, which in turn leads to growth and success of the company. Therefore, AI-powered predictive analytics and personalized experiences allows businesses to gain a competitive advantage by enabling companies to meet customer needs, anticipate market trends and stand out from the competition. Through these advantages, AI and ML are leading to significant improvements in terms of efficiency, encouraging innovation and strengthening competitiveness in various sectors. So, while AI can be defined as the development and training of computer systems to perform tasks and think like humans, ML is a subfield of AI that focuses on enabling computers to learn and act without explicit programming by processing data input. Businesses are utilizing AI and ML to address various challenges, such as reducing customer churn rates using ML to inform AI in making personalized offers tailored to specific customer needs. Furthermore, ML enables AI to process more nuanced data, allowing companies to seize new opportunities and accelerate business growth. Finally, AI can make complex decisions efficiently by leveraging the vast amount of data processed by ML at every stage of the process. In conclusion, AI is transforming the way businesses operate, innovate and compete in today's fast-paced, technology-driven world. AI offers a plethora of benefits, which enable businesses to reach new heights of success and unlock their full potential. With the ongoing advancement and maturation of AI, its influence on business will only continue to grow, paving the way for a future marked by innovation, agility and sustainable growth.  Thus, embracing AI as a strategic imperative, is not only crucial to remain competitive in the increasingly challenging global market, but also to achieve success and thrive. (How is AI different from ML, 2024; D'Acquisto G., 2021; Alpaydin E., 2012)

### 1.2 Overview of the Mergers and Acquisitions Industry

#### 1.2.1 General description of the M&A sector and its importance to businesses

M&A activity has increased tremendously over the past two decades, expanding the range of both domestic and cross-border transactions. M&A is an important part of the financial services industry. This category comprehends mergers, acquisitions, consolidations, and public offerings. While mergers indicate the combination of two or more companies to form a single entity and its goal is to integrate the resources, acquisitions refer to the purchase of another company, in which the target company comes under the control of the acquiring company expanding the customer base. Consolidations instead, refer to the merger of two or more companies into a single new entity, extinguishing the original companies. Finally, tender offers are a public proposal for the purchase of shares in a company by its shareholders.  The strategic reasons behind M&A may be market expansion, for beating market competition, for the cost synergies generated, increased shareholder value, for technological innovation, to consolidate the industry and diversification. Therefore, companies that perform such transactions wants to achieve economies of scale, enter new markets or new technologies, to increase competitiveness and accelerate growth. M&A also fosters innovation and accelerates technological advances; in fact, companies are looking to acquire technologically advanced start-ups to stay ahead of the curve and adapt to changing market dynamics as well as consumer preferences. In addition, M&As are a strategic tool for risk management as they allow portfolio diversification and thus reduce the risk of reliance on a single product or market. Another feature of M&A is that by pooling resources, it can lead to economies of scale and generate cost savings. Finally, the acquisition unlocks access to new financial resources and specialized skills present within the target company. The complex M&A ecosystem consists of various players with specific expertise such as corporations, legal advisors, investment banks, auditors, and private equity firms. Investment banks, such as the most prominent JP Morgan Chase and Goldman Sachs, is to facilitate M&A transactions by providing financial advisory services, finding necessary financing, and evaluating target companies. Due diligence services are provided by accounting firms through a detailed assessment of the financial health of target companies. Consulting firms target operational efficiency by offering advice on cultural alignment and post-merger integration. More and more boutique advisory firms are also springing up nowadays, which specialize on M&A transactions and offer industry expertise. There are several stages in an M&A transaction ranging from identification of potential targets, fair value assessment, negotiation stage where the terms of the deal are discussed, and due diligence procedures. In some deals, approval from government agencies must also be obtained before the deal can close and the last phase, the post-merger resource integration phase (where operational and cultural alignment is sought), can begin.

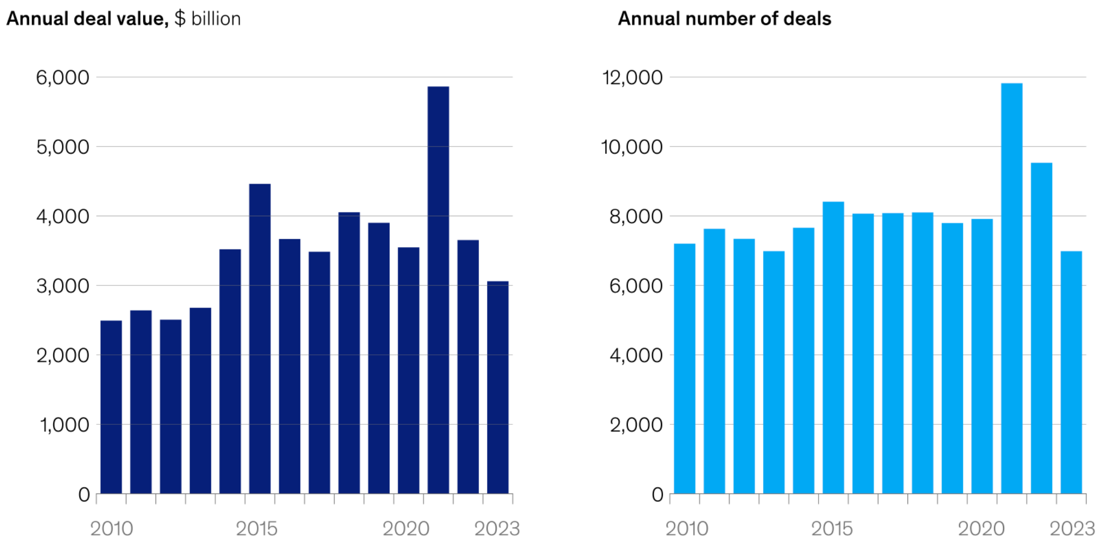
In recent years there has also been a growing trend for M&A involving emerging economies, mainly those that are growing rapidly. Emerging economies are increasingly globalized, and local companies entering the global market attract foreign companies. However, the M&A process can be uncertain and complex, and if some deals are no longer profitable, they are abandoned. M&A are constantly evolving and therefore are influenced by macroeconomic trends, regulatory developments and market dynamics. Macroeconomic changes, such as inflation, interest rates, exchange rates, and GDP, have different effects on the abandonment of M&A deals in different types of economies; M&As in developed economies are more stable about changes in macroeconomic factors, while M&As in emerging economies (belonging to the BRICS) are more volatile. Volatility in emerging BRICS countries indicate more uncertainty in M&As. This can be explained by a higher risk appetite for BRICS companies, which are looking for growth opportunities, while G7 companies show a more conservative risk appetite in M&As, with cautious decision making. In fact, G7 companies aim to acquire technology or consolidate the market, while BRICS companies want to expand and to improve their competitiveness through M&A. The different regulatory environment also influences strategic M&A decisions between G7 and BRICS, regulatory policies can affect outcomes. (Kumar, Sengupta, Bhattacharya, 2023).

In addition to increasing cross-border M&A activity, other recent trends in M&A are a growing focus on technology-driven transactions and thus digital transformation, increased interest in ESG (environmental, social and governance considerations) issues, and shareholder activism regarding corporate governance. In recent years, another factor that has certainly had a big impact on M&A activity is the COVID-19 pandemic, which has accentuated the fluctuation of deal volumes and led to an increased focus on risk management. In conclusion the M&A ecosystem is a complex environment that demands constant attention to competitive pressures and regulatory considerations. To succeed in this field, it is essential to keep up with the latest innovations and maintain a constant flow of information. M&A activity continues to shape the corporate landscape and stimulate economic growth, but it also poses risks such as cultural clashes between merging entities, overvaluation of target companies, and integration challenges.

### 1.2.2 Explanation of the growing relevance of M&A analysis in the current business environment

In the modern corporate landscape, M&A is an increasingly important step to grow, and this is due to a variety of factors, including changing industry dynamics and high transaction volumes. The trend of 2024 M&A activities is growing, to return and then surpass the pre-pandemic trend.

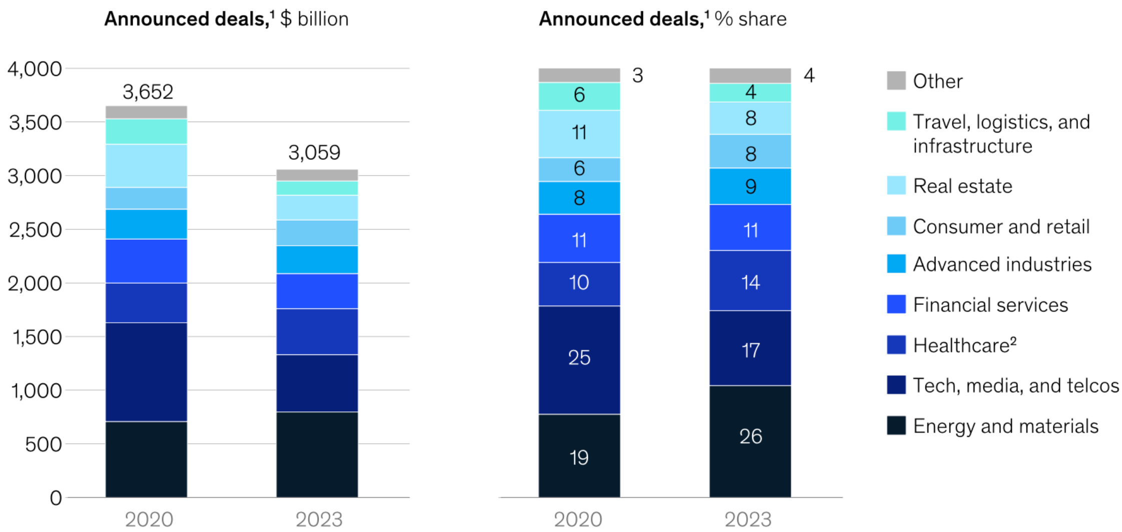
Chart 1: Compare between global deal value and volume in 2023 M&As




Top M&A Trends in 2024. McKinsey & Company report (2024), Henry J.

Here, there is a report of Mc Kinsey & Company on the recent trend of M&A activity in the past year. In 2023, global M&A activity exceeded pre-pandemic levels by reaching a record $5.9 trillion. Technology drives much of today's M&A and areas such as AI, cybersecurity and cloud computing attract huge investments.

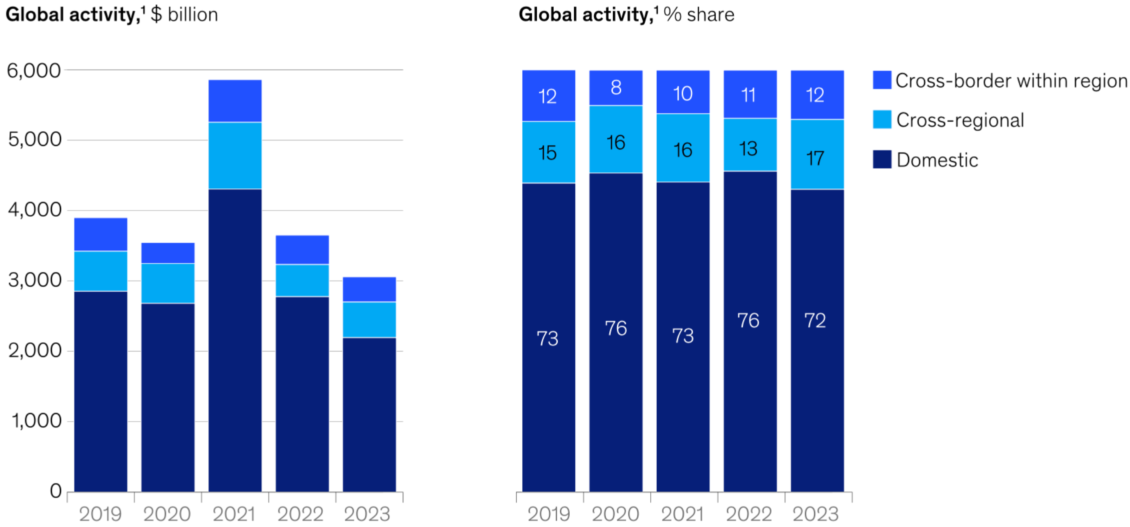
Chart 2: Value and industry share of M&A activity in 2023




Top M&A Trends in 2024. McKinsey & Company report (2024), Henry J.

These number are useful to understand what the average deal values were, while the second chart, shows the sectors with the most activity in this field. The visualization of these data is coherent with the average values founded in the data collection presented in Chapter two, leading to an interesting empirical analysis.

Chart 3: National, Cross-regional and Cross-border deals in 2023




Top M&A Trends in 2024. McKinsey & Company report (2024), Henry J.

The last chart, divided three types of regions to differentiate the geographical variety of M&As. In the empirical work in chapter two, there will be just two categorize of geographic distinction between national or cross-border deals, with the second one including also the cross-regional deals to simplify the data for the regressions.

In the recent period, there has also been a trend towards geographic diversification towards the Asia-Pacific region, which due to significant economic growth and strategic ambitions emerges as a major player, although the US and Europe, the traditional M&A hubs, retain a prominent role. As a result, cross-border M&A activity is increasing. A major advantage of M&A transactions is risk mitigation through diversification: it reduces dependence on a single market by diversifying revenue streams and broadening product portfolios (Henry J., 2024).

Recent examples of large M&As include, in 2023, Merck's acquisition of Themis Bioscience, fuelling M&As in the healthcare sector concerning innovative immunotherapies for cancer treatment. Previously worth mentioning is Microsoft's acquisition of Activision Blizzard in 2022, in which a record was set in the gaming industry, highlighting the metaverse's considerable importance. Furthermore, NVIDIA's rise as a major player in the future of computing started in 2020 with the acquisition of

Arm Holdings, which highlighted the growing demand for semiconductor technology and artificial intelligence capabilities. Moreover, in these past few months, the key message conveyed by the world's largest technology companies to investors was that they must invest billions of dollars every quarter in developing their AI products. Someone welcomed this move, others were skeptical. Microsoft and Google parent Alphabet experienced a surge in their share prices after they revealed that their increased spending was driven by the growing demand for AI products. Microsoft's CFO, Amy Hood, clarified that the capital investments were necessary to meet the current demand for their AI products, which exceeds their supply. In contrast, Meta Platforms witnessed its worst period in 18 months after announcing an increase of up to $10 billion in its capital expenditure projections for 2024, primarily to fund its AI development. CEO Mark Zuckerberg warned investors that they should brace for several years of aggressive spending before Meta can achieve substantial profits from its AI services. Microsoft has projected that it will spend $14 billion per quarter on equipment and property during its AI build-out, with the expectation that this figure will rise in the coming quarters. All this highlights the rush to adopt AI in the last period, where every day one must adapt to the changing environment (Dotan T., 2024).

This analysis evaluates market trends, financial metrics, potential synergies, and regulatory hurdles to assess the feasibility and potential advantages of a transaction proposal. By carefully examining potential transaction objectives and structures, M&A analysis minimizes risks and maximizes the likelihood of success. The growing significance of M&A analysis reflects the dynamic and ever-changing nature of the contemporary business environment. As M&A activity continues to flourish across industries and regions, robust analysis has become an essential tool for companies seeking to take advantage of strategic opportunities and create long-term value through successful mergers and acquisitions (Levi B., 2024).

## 1.3 The Role of AI and ML in M&A

### 1.3.1 Use of AI and ML in the M&A process

In M&A transactions the use of artificial intelligence is becoming a key element in several stages of the process. AI techniques are becoming necessary to navigate this new data-driven world, in this context AI optimize key milestones in the M&A lifecycle, allowing dealmakers to focus more on areas such as negotiation and stakeholder communication (L'Intelligenza Artificiale nell'M&A, 2024). The emerging technologies, including ML, large language models (LMMs) and other tools, are revolutionising the industry, becoming central to how M&A strategies are crafted and are no longer just supplementary tools (Moeller S., 2024). For dealmakers, the goal is to maintain a strategic advantage and to do this, it is essential to understand how AI is reshaping the M&A process. Because AI can quickly make a target firm's business model obsolete, there are fears of a loss of competitive advantage. This indicates that now, for target selection, it is also necessary to assess the company's ability to thrive and adapt in a rapidly changing technology panorama, and not just evaluate its current performance. In addition to potential threats, there are also great opportunities for value creation and growth (Nichol S., M&A Insights, 2024). A recent study by Accenture found that executives listed 'strategy and M&A' among the top three areas they plan to revolutionize in the next three years. According to Bain & Company's forecast, the use of generative AI in M&As is expected to reach 80 per cent in the next three years, although implementation is currently very low (just 16%). Generative AI is expected to improve M&A deal returns by a large margin, so the move towards its incorporation into M&A processes is expected to be rapid (AnsaradaWed, 2024). In Italy, for example, the market is segmented in multiple SME (Small Medium Enterprises – PMI) which are companies with relatively small size. The implementation of AI is helping to increase the number of M&A deals for these types of companies, bringing growth and development to the SME. By ensuring efficiency and accuracy, AI has quickly become an indispensable tool for streamlining M&A procedures to increase value by improving deal outcomes overall. There are five key areas in which AI can help increase the success of M&A deals: data analysis, target identification, business evaluation, due diligence and post-acquisition integration (M&A and Artificial Intelligence, 2023).

### 1.3.2 Discussion of how AI and ML can improve decision making in M&A

The first phase in which AI can be helpful is in the strategy for deciding whether to pursue a M&A transaction. To this end, AI can analyse large amounts of data from both companies involved in the transaction to ensure a more accurate assessment of challenges and opportunities. By analysing competitors' strategies, market trends and historical transaction outcomes, these technologies provide a data-driven approach to decide whether an M&A deal should be pursued, and doing so they are reshaping strategic decision-making in M&A. AI models are becoming sophisticated and, in the coming years, will have a significant impact in identifying strategic growth opportunities and predicting market movements (Moeller S., 2024). AI therefore performs a kind of 'treasure hunt' through deal sourcing. It is no longer necessary to manually sift through endless reports and data as, thanks to the power of AI, large amounts of market data, financial reports, news articles and even social media can be scanned for potential acquisition targets. Machine learning algorithms can detect that a company is a prime candidate for acquisition decisions by means of the patterns they detect and by analysing certain signals (AnsaradaWed, May 29, 2024).

The second moment and one of the most transformed areas of M&A is the target company identification of potential targets. Empowered by big data, AI algorithms can identify companies that match specific financial and strategic criteria, sifting through vast amounts of information. This process allows to discover opportunities that otherwise will be overlooked using traditional methods and this result in a more effective target identification. The conventional methods for identifying potential deals are not being used, as AI is able to analyse real-time data from sources such as Google searches, company balance sheets and market trends, to name a few. Thus, AI can quickly identify possible targets to solve needs that companies aim to achieve through extraordinary operations such as expanding into other markets or expanding the product ranges (L'Intelligenza Artificiale nell'M&A, 2024). Thanks to predictive AI analysis, current market conditions can be analysed and compared with historical data to predict future opportunities. Analysis of market trends and company performance can thus be predicted, which can help investment bankers make more informed decisions (AnsaradaWed, 2024). Another part in this phase is played by 'advisors'. The use of expert advisors is a key part of the M&A process, and the integration of AI and automation will increase the capabilities of these professionals, such as accountants, lawyers and investment bankers. For example, AI has had an impact in complex financial modelling or in the review of legal documents, with some organisations already experimenting with it (Moeller S., 2024). Looking at the Italian landscape, with AI SMEs can increase the chances of a successful transaction by identifying acquisition targets that meet specific requirements and strategic alignments. Thanks to new technologies such as machine learning, potential acquisition targets can be explored and their impact on financial performance assessed (M&A and Artificial Intelligence, 2023).

Another area where AI and ML have a profound impact is valuation: here, advances in technologies enable more accurate valuations by analysing a multitude of factors such as company performance, projections of future growth and market conditions. A significant advantage brought by AI-driven models over traditional methods is that they can continuously update valuations in real time (Moeller S., 2024): by integrating real-time data and advanced analytical models AI improve the accuracy of business valuations. Typically, the valuation of a company is done by means of three different types of approaches such as revenue-based, cost-based or market-based. Here, AI can develop real-time databases as a basis for evaluation and it is also useful as a data collection tool for forecasting activities, and it can analyse the past performance of the target company so that SMEs can evaluate their hypothetical future in a more objective way (M&A and Artificial Intelligence, 2023). The valuation of the target company is a crucial step in the M&A process, as any mistake, such as an over- or undervaluation of the company, can negatively affect the entire transaction. In this context, AI makes it possible to gather essential data for the valuation and avoid potential human errors: by analysing historical transaction data, financial metrics, and industry benchmarks, it generates a vast amount of crucial information to provide a correct valuation of the target company. For example, AI proves to be a valuable resource for identifying the multiples at which companies comparable to the target are valued using the market multiples method. This approach improves valuation accuracy as it simplifies data retrieval and provides a broad and accurate perspective on market performance (L'Intelligenza Artificiale nell'M&A, 2024). This results in more effective negotiations and fairer transactions. In addition, AI performs analyses of alternative scenarios, resulting in more strategic decision-making and better preparation during negotiations. By simulating various transaction scenarios and their potential outcomes, gen AI helps dealmakers understand the implications of different strategies and conditions to achieve the best possible decision after exploring countless options and fully understanding the outcomes of each. (AnsaradaWed, 2024).

The 'negotiation' between the two parties is a nuanced process because it relies heavily on interpersonal skills and human judgment, that are coloured by emotion. Therefore, this phase will remain less affected by AI because it needs a human approach; however, AI can still support this process by providing detailed analysis of market conditions and previous deals. For this reason, having an effective communication (with the merging companies internally and with key stakeholders externally) is crucial during an M&A transaction. AI can implement the analysis of communication strategies and affect the stakeholder sentiments, but in this stage the process of communicating is still poorly influenced by AI. The empathy and the ability to understand human emotions in communication are something that AI cannot fully replicate. Therefore, human experience and empathy allow for building trust, making connections, and managing complex negotiations. Target identification, Valuation and Due diligence will be deeply impacted by AI, while stakeholder communication and negotiation still need a human touch. So, AI should not be regarded as a substitute for humans but as a complement to them; through its help we can improve productivity at both the individual and organizational levels and make more informed decisions. Thus, to be successful, the integration of technologies in M&A requires a shift in thinking, other than the adoption of AI. Firms that successfully leverage these technologies will enjoy a substantial competitive edge in the continuously changing M&A environment. (Moeller S., 2024; L'Intelligenza Artificiale nell'M&A, 2024).

Then there is a considerably challenging phase: due diligence. It is critical for a successful transaction, but it is no secret that it can be very long and tedious. A considerable amount of time and resources must be invested here, as a thorough analytical review of multiple critical aspects of the target company is needed. AI in this context allows the process to be significantly simplified as it enables the automation of the analysis of massive amounts of data, including legal documents, financial statements and market research. This speeds up the process and allows for greater precision in the identification of risks and opportunities, so that the focus can be shifted to more strategic and decision-making aspects (L'Intelligenza Artificiale nell'M&A, 2024). Due diligence has great impact, especially for Italian SMEs, often being a significant barrier to accessing M&A opportunities. With the introduction of AI, a large part of this process can be automated through machine learning algorithms and advanced analytical tools thanks to which a wide range of financial, legal and operational data are quickly examined, leading to a reduction in the time and costs required to assess the purchase of a potential target company (M&A and Artificial Intelligence: possible scenarios for the future of SMEs, 2023). In this field, it has been introduced the use of virtual data rooms (VDRs) because of the vast amount of data that can be stored in those VDRs. AI and ML conduct the due diligence at a speed and depth that are not possible by human teams. This includes risk assessment, financial analysis and evaluating the potential cultural fit between the two companies. In identifying risks and opportunities, Natural language processing (NLP) algorithms can make the job easier for the team, helping extract key information from documents. NPL can automate the examination of huge volumes of documents: AI ensures compliance with regulatory requirements, extracts relevant information and detects red flags. This accelerates the due diligence process and reduces the risk of human error. In the due diligence phase, another key moment is risk assessment: AI systems can assess the financial, operational and strategic risks that are associated with potential transactions by analysing historical data and identifying patterns. AI highlights areas that require further investigation through a comprehensive risk assessment that brings hidden details into focus. The due diligence phase is one of the most transformed by AI and automation (Moeller S., 2024; AnsaradaWed, 2024).

At this point the deal is finalized, the AI here enables the automation of various administrative tasks in the transaction (e.g., performs compliance checks, compiles regulatory documents, and coordinates the parties) and thus allows the professionals involved to focus on more valuable activities. This change requires advisors to adapt their skills, because instead of focusing on data collection and analysis, they will need to improve their abilities in areas such as critical thinking, data interpretation to focus management teams' attention on important value drivers. One of the tools powered by AI is blockchain technology, which is introducing NDAs, smart contracts that, when certain predefined conditions are met, are self-executing. This method reduces the time and cost of closing the deal and at the same time, provides full transparency (Nichol S., M&A Insights, 2024).

Finally, there remains the phase that often turns out to be the most complicated and delicate in an M&A deal: post-merger integration. When the agreement between two companies has been concluded, the merging of resources and personnel, as well as the activities of the two companies, takes place. Again, this results in numerous operations for which we can leverage artificial intelligence: it facilitates the integration by making predictions regarding the cultural and operational fit between the two companies. Alignment strategies and potential conflicts are identified by AI through analysis of factors such as workflows, employee sentiment, and communication patterns. The result can highlight a successful merger, or a potentially problematic union. AI also enables real-time monitoring of merger performance to indicate areas that require more attention for the integration process to be successful, to stimulate growth within the combined organization. This allows for health checks of the new entity and faster responses to emerging issues in real time. (AnsaradaWed, 2024; M&A and Artificial Intelligence: possible scenarios for the future of SMEs, 2023). Therefore, the focus of the managers responsible for the transaction can leverage the data collected by AI in both companies to develop effective post-transaction strategies. Actually, now M&A professionals should be introducing more AI, but they aren't doing it yet. So, the future of M&A is inevitably associated with advancements in AI, and one example of a company that has applied AI in the context of extraordinary transactions is M&A Research Institute Holdings (L'Intelligenza Artificiale nell'M&A, 2024; Moeller S., 2024).

The solutions offered by data analysis using AI can identify additional opportunities for value creation, for example by analysing the potential synergies and risks of the companies involved to discover the most efficient method of integration. The goal of M&A is to create synergies, leverage complementary strengths and opportunities between the merging companies, so AI-based tools generate detailed estimates of expected synergies and thus assist operators in designing optimal transaction structures. Generative AI enhances this process and builds operational efficiencies or new market expansion strategies that neither company would otherwise achieve individually. Generative AI constantly generates new ways to create value, new ideas, and solutions based on existing data to foster innovation within the merged entity. This enables long-term growth a competitive advantage (AnsaradaWed, 2024). Although new scenarios will open in the future, AI is rapidly transforming an essential part of our working world and is already having an impact in financial operations, as evidenced by a Deloitte report that found nearly 70 percent of surveyed M&A executives consider ESG (environmental, social, and governance) and EHS (environmental, health, and safety) elements to be of high strategic importance when evaluating potential transactions. Moreover, due to the legal and financial risks associated with non-compliance, EHS considerations are becoming increasingly essential. M&A industry is employing AI solutions to meet EHS and ESG due diligence needs, because by conducting due diligence on the target company's EHS compliance, the acquiring firm can reduce risks and protect its reputation, to enable a smoother M&A process. (M&A e Intelligenza Artificiale, 2023; The Impact of AI on M&A, 2024).

### 1.4 Due diligence

The integration of AI into the due diligence process has far-reaching implications. The AI revolution is in progress and has already transformed the way law firms conduct due diligence, making it faster and more efficient. AI's superior ability to analyze documents has eliminated the need to spend countless hours on labor-intensive tasks, freeing up time and resources to focus on value-added services for clients. The quality of the work has also improved, with deeper searches and more faster document analysis. This has enabled legal teams to conduct more accurate diligence reviews in a shorter timeframe with lower costs. While uncovering potential risks reviewing thousands of documents in few minutes, AI can reduce the document review time during due diligence by up to 70 per cent on average (O'Learly C., 2023). Therefore, AI can enhance the due diligence process by increasing efficiency. By analyzing vast datasets, AI algorithms can improve the accuracy and reliability of assessments by identifying patterns, anomalies, and trends. As a result, stakeholders can make informed decisions, mitigate risks, and capitalize on opportunities in dynamic business environments (Amell S., 2024).

In the next chapter the goal will be to delve deeper into the M&A process to perform empirical analysis and show how AI can mitigate risks and simplify the process. Our hypothesis is that the adoption of AI and ML techniques led to an efficient deal conclusion, with accurate assessment of the target company, risk evaluation to adjust M&A decisions. This research by employing quantitative analysis aims to compare the risk profiles and post-merger performance in M&A that utilized AI and ML techniques on risk assessment against those transactions that relied on traditional methods. Research on AI and M&A proved that AI could help streamline the due diligence process, yet a gap in the literature exists regarding the specific influence of AI within the total deal. This study aims to address this gap by examining how AI/ML can enhance the quality and efficiency of the overall process. The goal is to understand the role of AI in providing a more comprehensive view of the deal with the characteristics of both companies involved, to understand how specific features like the size of the deal, the company age or the prior M&A experience of the firms can affect the performance of the transactions.

**Conclusion**

This chapter has explored the potential benefits of the application of AI and ML in various industries, with a particular focus on the M&A process. Through automation, predictive capabilities and data analysis, AI can significantly improve efficiency and reduce human error across the different stages of M&A deals. allowing companies to make more informed decisions and complete deals faster.

One of the most impactful areas where AI can provide immediate value is due diligence that is a process that requires lots of time and intense labor-intensive. AI-driven tools can rapidly analyze large sets of financial, legal, and operational data, impacting the time to complete this phase and the resources required.

While theoretically the benefits of the introduction of AI in M&A are infinite and clear, the real challenge lies in quantifying its impact on deal efficiency and performance. In the past few years, the positive effect of AI in M&A deals has been proved only in the due diligence phase. The second chapter try to address this gap in the existing literature and focus on performing empirical analysis of real-world data. The chapter aims to provide concrete evidence of AI’s effect on deal efficiency by analyzing a small but heterogeneous sample of M&A transactions. Through regression models, we will assess the relationship between the use of AI and key M&A metrics such as time to completion and cost efficiency, thus offering empirical support for AI's role in improving M&A processes.

# CHAPTER II
# AN EMPIRICAL ANALYSIS ON M&A WITH DATA FROM BLOOMBERG

## Introduction

In this chapter, after reviewing the theory behind the application of AI in the world of M&A, we come to the heart of the research: the empirical analysis. By employing various econometric models, the aim is to evaluate how the introduction of AI systems in the companies of different industries helps to improve and accelerate the M&A process, specifically two critical aspects of it: the Time to Completion and Cost Efficiency. The integration of AI technologies should theoretically simplify transactions both because they process the information in a faster way – hence reducing transaction costs - and because more information can be gathered in a short time, hence reducing asymmetries of information. The purpose of this chapter is, by investigating these two specific factors, to try to quantify the positive or negative impact on the transaction through the analysis of real-world data. The results of a positive intervention can be seen through reduced transaction time or, for example, improved efficiency in resource allocation during M&A transactions.

The challenge is to set up a model that properly captures the main drives of the time to completion and the cost-efficiency, by taking into account of the differences across firms and transactions.

The first stage of the analysis focuses on modeling Time to Completion as a dependent variable, using real world data about the use of AI, the size of the companies involved and several control variables. With these assumptions, AI is expected to reduce the time required to complete the deals (from announcement date to closure) by introducing automation process and enhancing decision-making efficiency, speeding up the transaction. The second stage examines Log Value as the dependent variable to explore the relationship between AI and the deal size, aiming to understand how the complexity of the deal influences the M&A process. This is based on the assumption that larger deals are likely more complicated and associated with higher costs.

Therefore, this chapter presents an empirical analysis that aims to demonstrate the positive effects of AI on M&A processes. The results of the regressions should provide insights into how AI can be leveraged and integrated by companies to achieve faster and more efficient M&A transactions, ultimately contributing to improved strategic outcomes for companies involved in such transactions, not only at a preliminary due diligence stage but throughout the entire transaction.

### 2.1 Literature Review

In this paper, there has been the review of several papers on M&A performance. Unfortunately, these papers show often unique measures to study and interpret the M&A performance. More importantly, almost every paper had several unique variables that have been used as explanatory variables in these studies, because each one had different demonstration purposes. The reasons behind this many ways to measure and study the M&A performances are that these transactions depend on an infinite combination of several variables and that performance, like other organizational constructs, does not have a universal definition and depends on the questions the researchers intend to answer.

The past research that will be mainly taken as reference is that of Moeller et al. (2004); Ma W., Ouimet P., Simintzi E. (2016 and 2022), Healy et al. (1992); Lappi J. (2024); Ding Y et al. (2024), Nagasha et al. (2022) Schiffbauer et al. (2017); King et al. (2004), Ismail et al. (2011), Parikh et al. (2024).

Moeller et al. investigates the relationship between firm size and shareholders gains from acquisitions. This research highlights that smaller firms have better outcomes in acquisition than larger firms in term of returns. Even though this paper does not cover AI in M&A, it provides empirical insights into the impact of firm characteristics on acquisition success. This directly link to my hypothesis regarding AI and Time to Completion as shows how firm-specific factors influence as a key variable deal efficiency and acquisition outcomes. Then the paper of Lappi J. regards how AI is transforming the Due Diligence Process in M&A. This is an expensive phase in the transactions, in term of time and costs, requiring manual review of vast amounts of documents, financial statements, and legal records as we saw in Chapter one. AI technologies, automate many of these tasks speeding up the M&A, reducing the cost involved in due diligence and helps to enhance risk management, through the identification of red flags and potential risks. Moreover, AI systems can improve the overall quality of the due diligence process. To identify and fill the gap in the existing literature this work starts from these theoretical considerations to include also an empirical analysis of these claims on how AI can improve the entire M&A process by considering together all the phases that compose it. This paper is highly relevant also because it directly addresses one of the core variables in the empirical analysis: Time to Completion. The research of Ma, Ouimet and Simintzi is about the technological change and inequality in the M&A deals. The authors provide empirical evidence on how M&As influence job markets through technology adoption, directly addressing the relationship between M&A and technological change. The research shows how M&As lead to larger firms, which can more easily adopt new technologies, reduce financial constraints, allowing firms to invest in technology and acquirers may improve overall efficiency bringing to targets best practices in technology adoption. This paper is relevant as ties into how technologies in general can bring deal efficiency and cost reduction. The authors worked together also in 2022 providing empirical evidence from U.S. industries and argue that M&As act as a catalyst for technology adoption, improving efficiency but widening inequality. This ethical discussion on how technological adoption post-M&A improves the process with a potential threat to human labor will be explored more fully in Chapter four. Healy et al. investigates post-merger accounting data, particularly focusing on how M&A improves firm performance. The relevance of this paper is because its findings on the relationship between transaction characteristics and operating performance in the post-merger phase, directly link to the variables of firm size and transaction characteristics included in my analysis, that may influence the Time to Completion. Then there are three articles about the empirical evidence of how the cross-border M&A can affect the digital innovation. One focuses on Chinese Listed companies (Ding Y., 2024); one investigates the effect of M&A on firm performance in East Africa (Nagasha et al., 2022); and the last focuses on the productivity of acquired firms using data from the United Kingdom (Schiffbauer et al., 2017). While these paper focuses more on digital innovation and cross-border M&A networks rather than AI directly, they offer insights into how M&A transactions influence innovation. The authors find that cross-border M&A positively impact long-term digital innovation through resource acquisition and information exchange, though short-term effects are minimal. Studies focus on the environmental uncertainty that moderates these effects and highlight the heterogeneity of the impact of M&A networks by industry, firm size and top management characteristics. The heterogeneity of the variables on which M&A depend is a key feature that my empirical research also found. Then, the research from Ismail et al. reviews empirical studies on M&A performance, focusing on factors that explain why some M&A transactions succeed while others fail. The authors include in their analysis several factors that influence M&A performance, including method of payment, firm size, and industry features. This article provides a broad perspective on the factors that influence post-merger success, and many of these variables are interesting to study regarding the efficiency of the operation and the role of AI. Hence the relevance to my study. To understand the previous studies about M&A, the research from King et al. reviews the existing literature on how M&A impacts corporate performance, exploring several factors that affect post-M&A performance, such as the method of payment, firm size, industry type, and cross-border vs. domestic deals. The review shows that there are mixed findings on whether M&A improves long-term performance: some studies showing gains while others highlight performance declines. This paper covers many of the variables I have included in my work and provides a solid theoretical foundation to the real-world data I have chosen to analyze. Parikh et al. Finally, considered focuses on the integration of AI and natural language processing (NLP) into M&A processes, highlighting the creation of "AMP" (Accelerated M&A Processes). It analyses how AI and NLP can be used to enhance due diligence and optimize decision-making. The article shows AI's ability to streamline M&A processes, improve accuracy in identifying risks and opportunities and reduce completion times, through the analysis of case studies. The paper offers empirical insights on how AI can revolutionize traditional M&A processes and directly aligns with the goals of this research in evaluating how AI can improve M&A efficiency, in terms of reducing time to completion and enhancing cost efficiency.

In summary, the validity of this research is strongly supported by existing scientific literature, as most of the reviewed articles that focuses on empirical findings use OLS regression as a central econometric technique, reinforcing the methodological soundness of this study. Furthermore, many of the variables I have included in my analysis (such as firm size, type of payment, deal characteristics, and cross-border effects) are similarly used in other empirical studies, showing their relevance in evaluating M&A efficiency. This research also establishes a clear link with past literature by further extending the discussion on the role of AI in M&A. While previous studies have provided theoretically how AI can improve M&A deals and empirically just in specific phases, such as due diligence, there remains a gap in empirical evidence regarding AI's overall influence on M&A performance. This study addresses this gap by examining the broader impact of AI, focusing on Time to Completion, thus contributing to a more complete understanding of how AI affects the outcome of a deal.

### 2.2 Considerations on sample selection

Given the difficulty in publicly sourcing data regarding M&A deals as well as the inherent complexity of these deals, which are represented by huge amounts of data, several constraints were initially imposed to arrive at the final sample selection. To be able to significantly narrow down and make the amount of data manageable, M&A deals had been filtered based on several characteristics:

- Deal must be Completed
- Transactions occurred from 01/01/2019 to the present (last 5 years)
- Geographic area (deals done in Eastern Europe, Western Europe, and North and South America)
- Sector/ Industry
- Minimum deal amount of at least one hundred million
- Buyer and Target companies are both publicly traded companies

Limitations such as the period were set to analyze current trends in the M&A world, while the requirement that both the target and the buyer must be listed is justified by the greater availability of information on listed deals. The threshold of a minimum deal amount is needed because there is a tendency that the larger the deal, the more information that can be found. In addition, if the firms were too small in the database, information on the presence of possible synergies, which is important data for regression, would be missing. However, the data downloaded from the Bloomberg terminal made available by the university were difficult to manage since, even after this major skimming, more than eighteen thousand cases remained.

We therefore decided to change strategy and obtain a much smaller sample but one that contained all the available information needed for each individual transaction. The idea was to start with the analysis of a small but very representative, and therefore very heterogeneous, sample and then go on to perform Monte Carlo simulations to enlarge the sample and create noise around the starting distribution. So, the search parameters changed a lot, and this time data were obtained from the Bloomberg terminal regarding 140 deals of heterogeneous companies with characteristics that made the sample very diverse, from different geographic areas and different industries. A broader time horizon was also set to include deals from the past two decades, from 01/01/2004 to the present, and both public and private companies were included. In addition, to make the empirical analysis more objective, only traditional M&As were selected, excluding other forms such as Investments (transactions such as equity or financing), Spin-offs (transactions in which a company creates a new separate entity by divesting part of its business), Buyback or Buyout transactions, so as not to distort the results of the analysis. Finally, the lower bound for deal amount was also removed, to increase the random selection of the sample.

The information reported by Bloomberg regarding each deal, however, was incomplete, and a great deal of work was required to find specific data regarding each deal (such as the market cap and revenue of the companies involved, whether or not there was the use of AI, the time of deal completion, the age of the companies at the time of deal closing, or the companies' previous M&A experience). The sources used to find this information were many: reports from Bloomberg, articles from the Financial Times, reports from the S&P 500, Market Screener, Merg, Stock Analysis, from reports published by the Security Exchange Commission (SEC) in the case of U.S. companies, and, finally, from individual company websites and reports.

### 2.2.1 Description of the Dataset

The dataset used for this study contains detailed information about every M&A operation, including financial, geographic, and strategic variables. The dataset includes several binary, categorical and continuous variables that describe various aspects of the transactions, such as the value and the size of the companies involved, the geographic locations of the buyer and target, the payment methods used, and the time to complete the deals. For some key variables it is useful to see mean and distribution so that some considerations can be made:

- Time in the Market of Acquirer and Target: This variable captures the number of years the acquiring and target companies have been operating in the market at the time the transaction was completed. It provides insights into the experience and maturity of the companies involved in the M&A transactions. The average time in the market for acquiring companies is 54 years while the one for target companies is just 38 years, this shows that on average the acquirer is older than the target and though it is plausible to presume that has also much prior M&A experience. In both acquirer and target companies there is a great variation in standard deviation values, indicating a wide range in the companies’ age. The value 1 as minimum time in the market, is a conventional value justified from M&A deals happened few months after the birth of the company.

Table 1: Company age at the time of the deal

| | Time in the Market (Company Age) in Years Acquirer | Time in the Market (Company Age) in Years Target |
|---|---|---|
| count | 140.0 | 140.0 |
| mean | 54.035714285714285 | 38.06428571428572 |
| Std | 52.483832483422894 | 42.44339619753689 |
| min | 1.0 | 1.0 |
| 25% | 19.75 | 10.0 |
| 50% | 34.0 | 22.0 |
| 75% | 73.25 | 73.25 |
| max | 338.0 | 338.0 |

Own calculations from sample data.

- Gross Domestic Product of Acquirer and Target: This variable measures the GDP growth rate (in percentage) of the countries where the acquirer and target companies are located, in the precise year when the deal was conducted. Therefore, it is a valid indicator of the economic conditions in which the transaction take place and helps understand how the macroeconomic environment has affected the success and the total value of deal.

Table 2: Gross Domestic Product (GDP)

| | GDP Acquirer (%) | GDP Target (%) |
|---|---|---|
| count | 140.0 | 140.0 |
| mean | 0.027023571428571428 | 0.026218571428571428 |
| Std | 0.028208845009915287 | 0.028382496850011353 |
| min | -0.054 | -0.098 |
| 25% | 0.016 | 0.01775 |
| 50% | 0.02465 | 0.024149999999999998 |
| 75% | 0.03425 | 0.03425 |
| max | 0.142 | 0.142 |

Own calculations from sample data.

- The interesting information here is that the average GDP of the buyer is slightly higher than the average GDP of the target, this is because in the 140 transactions examined, many involve cross-border transactions, and of these almost all the transactions had the buyer coming from a country with better economic conditions. In addition to transactions within the same continent, a portion of the cross-border transactions are between developed countries investing in target in poorer countries with significantly lower GDP. The average GDP Acquirer is 2.7%, and the average GDP Target is 2.6%. The positive percentages indicate that, on average, the countries of both the acquirer and the target are experiencing moderate economic growth. The median of 2.46% and 2.42% are close to the mean, suggesting that there is no extreme skewness in the data. There are also some countries experiencing recession or negative growth at the time of the deal as shown by the minimum values.

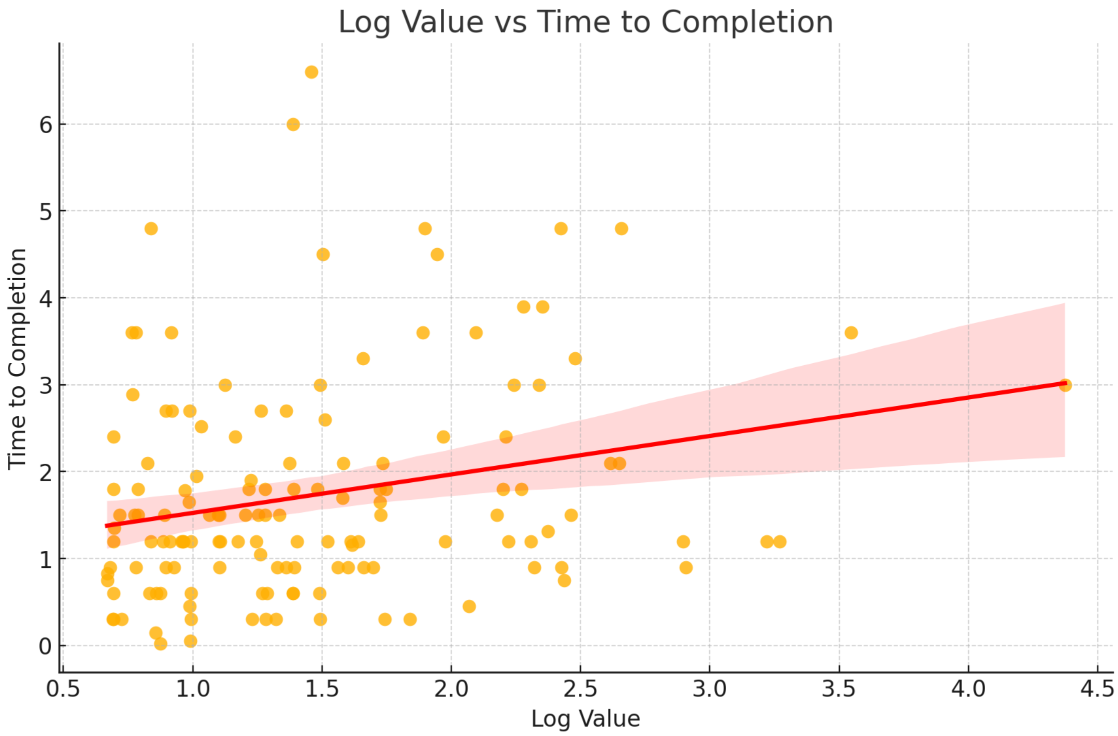
- Use of AI: This variable indicates whether AI technologies were used during the M&A process (0 = No, 1 = Yes). It was particularly difficult to find this information because the integration of new technologies is still a relatively new phenomenon and most companies do not publicly disclose whether they are implementing them or not. The dataset shows that 28% of deals involved the use AI.
- Time to Completion: This indicates the number of days it took to complete the M&A transaction. The average time to completion is 173 days, with a median of 150 days. For calculation purposes it was divided by 100.

Table 3: Time to Completion

| | |
|---|---|
| count | 140.0 |
| mean | 1.731142857142857 |
| Std | 1.2419803666900602 |
| min | 0.02 |
| 25% | 0.9 |
| 50% | 1.5 |
| 75% | 2.175 |
| max | 6.6 |

Own calculations from sample data.

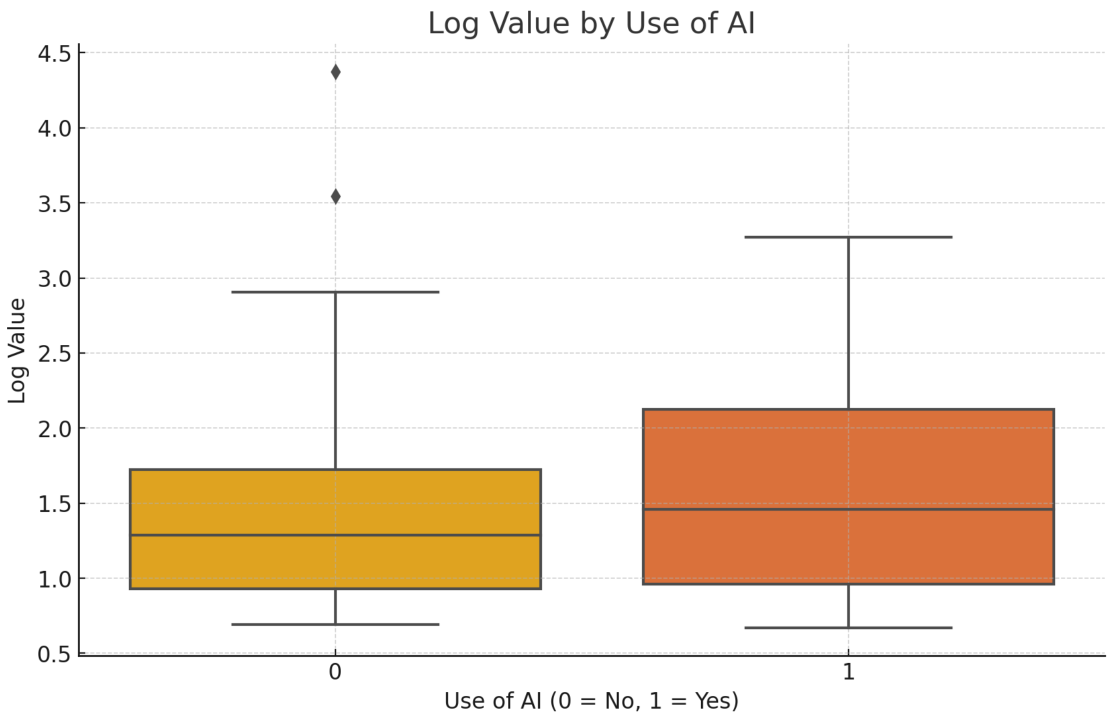
Chart 4: The relationship between Log Value and Time to Completion




Own calculations from sample data.

The graph shows the relationship between the two variables: the regression line in red indicates a slight positive correlation and that there is a weak trend that operations with higher value tend to have longer completion times, although this relationship is not particularly strong. The point dispersion is significant, with a wide variation in completion time for the same Log Value interval. This suggests that other variables may have a greater influence on completion time. Despite the positive trend, there is significant variability in completion time for lower-value deals. The pink area relates to the confidence interval, that widens for higher Log Value values, indicating that there is greater uncertainty in predicting completion time for higher value operations. This graph allows us an easy visual interpretation of the distributions and the trends, providing a clear view of the relationship between Log Value and Time to Completion.

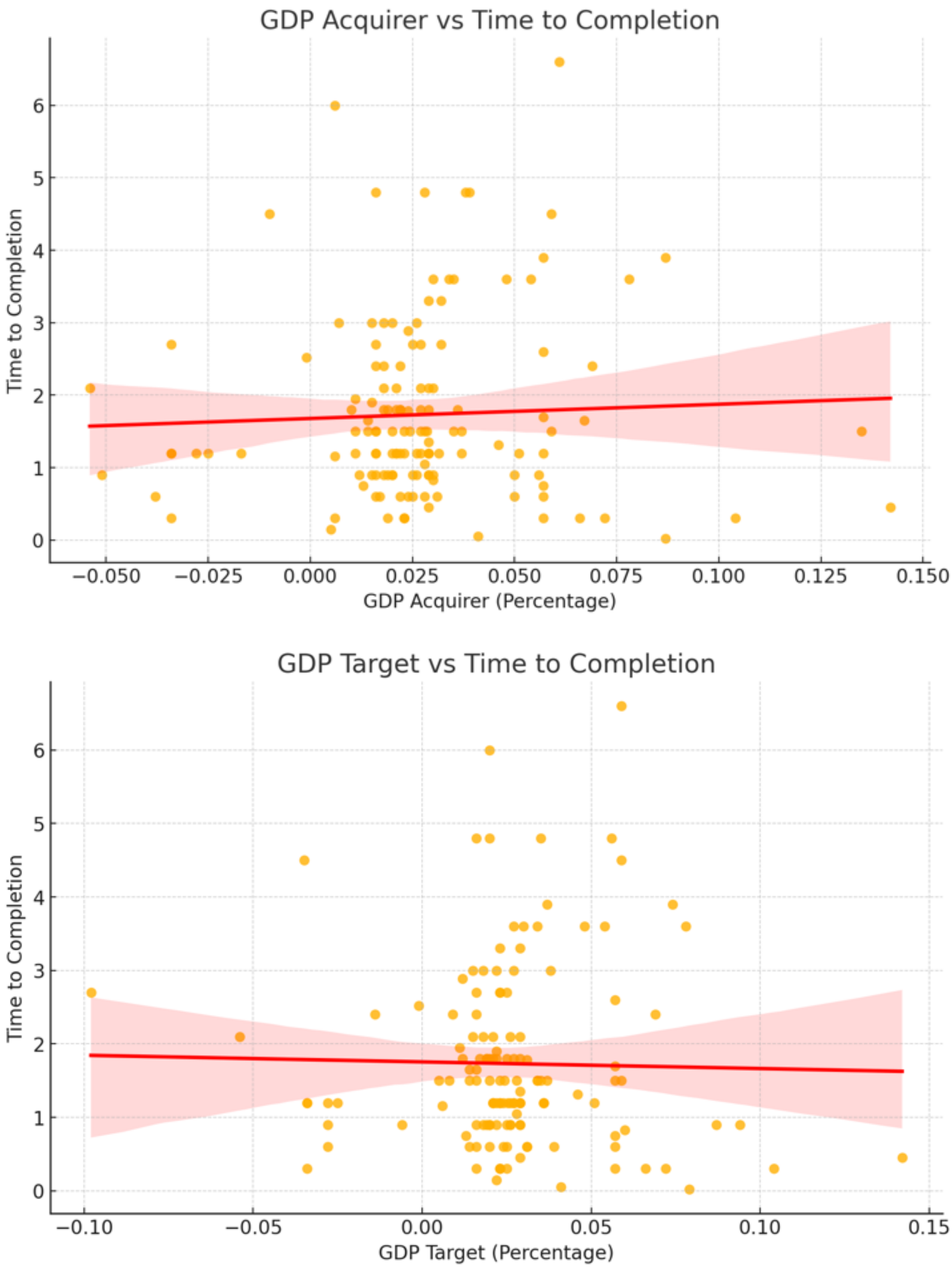
Chart 5: The relationship between Log Value and Use of AI




Own calculations from sample data.

Here, operations without AI have a lower median logical value than those using AI. This may suggest that operations in which AI is used tend to have higher values. The distribution shows that operations without AI have greater variability, with some outliers indicating very high value operations (nearly 4.5), maybe referring to deals concluded in the first decade of the 2000s when AI systems were not implemented in M&A process and were not integrated in companies' tasks. Operations using AI have less variability in extreme values, showing a more compact distribution and no significant outliers. The interquartile range is slightly wider for operations using AI, suggesting a higher concentration of high logarithmic operations. In general, it appears that operations in which AI is used tend to have a higher log value than those in which it is not used. Although there are outliers for operations without AI, operations with AI have a higher median and narrower distribution, suggesting that the introduction of AI in M&A deals may be associated with more expensive, complex or larger transactions.

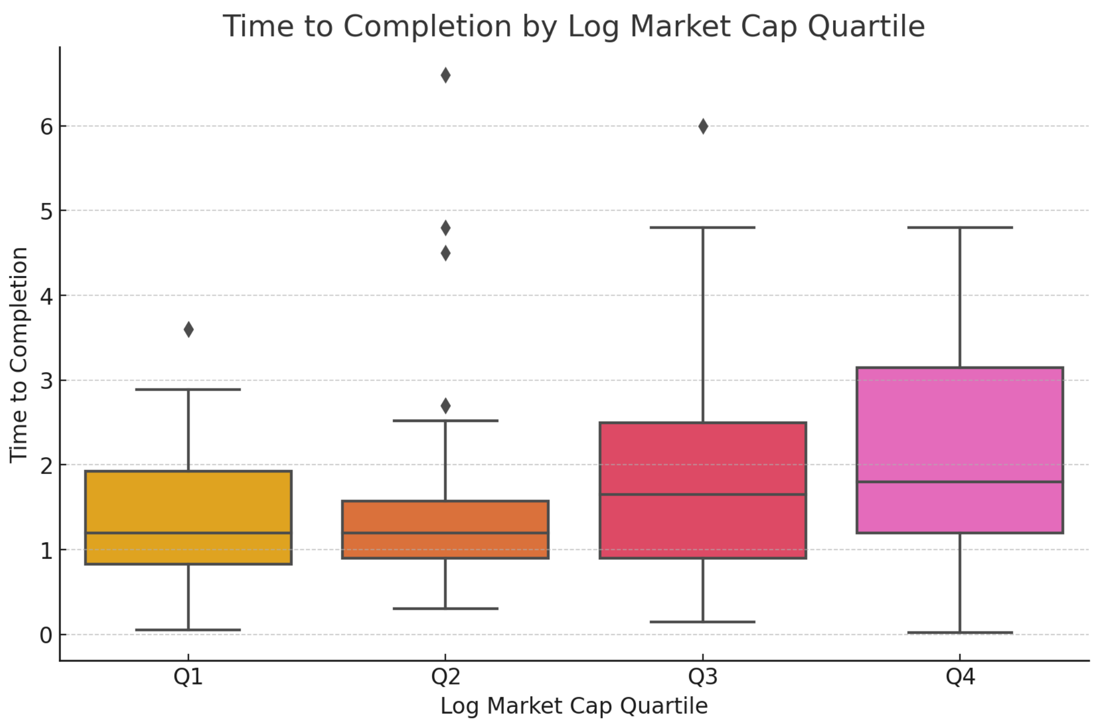
Chart 6: GDP Acquirer and GDP Target vs Time to Completion




Own calculations from sample data.

These two graphs show the relationship between the GDP of a country and the M&A deal concluded under that condition. In the first one, the regression line shows a slight positive slope, suggesting that as the GDP of the acquirer company increases, the Time to Completion tends to increase slightly, likely because associated with big deals in developed countries. However, since the slope is very weak, the correlation is minimal. Most of the data points are concentrated around 0% change in GDP, with some observations extending to a very extreme cases probably due to a GDP of a country in strong recession, like much of European and American companies during Covid-19 in 2020 and 2021. Despite this dispersion, the correlation remains very low. The pink area shows a wide confidence interval, suggesting that there is significant uncertainty in the forecast, especially for buyers with extreme GDP values. In the second graph is shown the same relationship but with GDP of the target companies, that we saw in the Table 2 has smaller value in mean. Here, the regression line is virtually flat, indicating that there is no significant relationship between target GDP and Time to Completion. There is no clear correlation with time to completion is observed and, also here, the confidence interval becomes very wide for extreme values of GDP Target, suggesting that the relationship between these two variables is weak and uncertain. Both graphs show a weak correlation between the GDP of the acquirer and the target and the Time to Completion of the M&A deal. This suggests that the GDP of the buyer's or target's country is not a relevant factor in determining how long a merger or acquisition deal will take to complete but the wide confidence intervals indicates that there are many other factors that may influence Time to Completion besides GDP. This analysis confirms that macroeconomic variables such as GDP may have little impact on specific aspects of M&A transactions because they depend on several conditions, suggesting that it is useful to consider other factors more directly related to the business process.

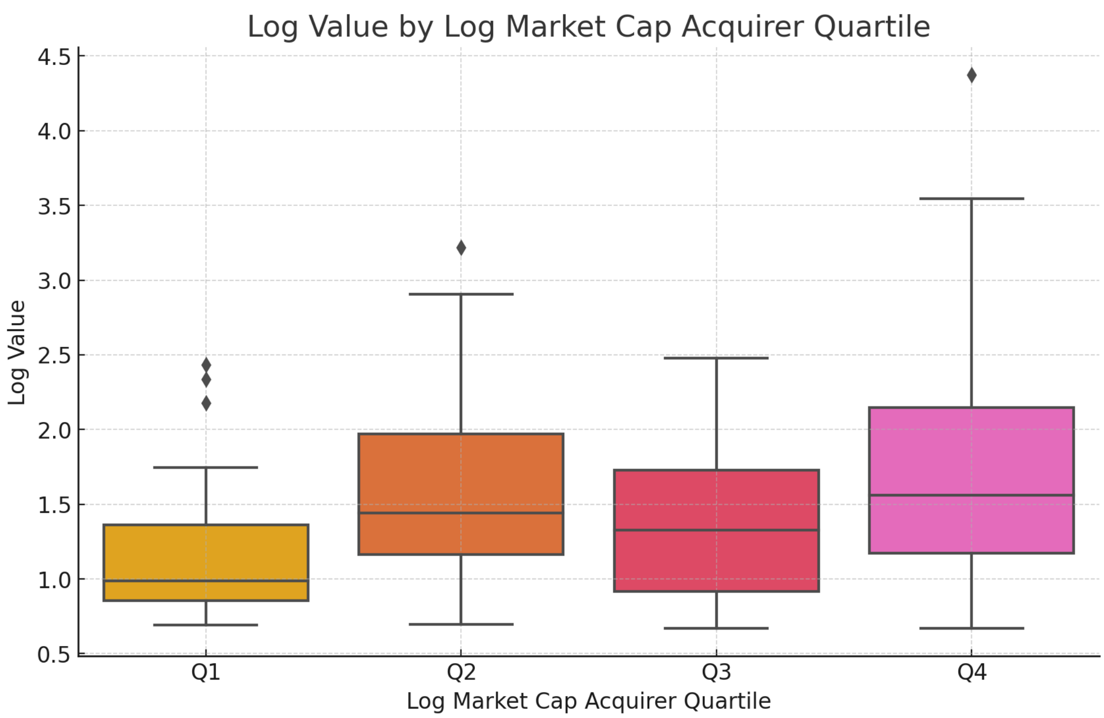
Chart 7: The relationship between Time to Completion and Log Market Cap Acquirer




Own calculations from sample data.

There can be several methods for estimating the effect of Time to Completion on firm size. As a reference to the size of a company, the logarithm of Market Cap and the logarithm of Revenues are used in this thesis, separated by Acquiring company and Target company. In order not to load multiple graphs that are very similar to each other, the relationship between the Time to Completion of the deal and the Log Market Cap of the Acquirer will be taken as a reference here. In the first quartile, companies with the lowest Market Cap tend to have a lower average time to completion, with a median slightly above 1 (so 100 days). In the middle quartiles (Q2 and Q3), Time to Completion tends to be lower, with medians close to 1, and less dispersion than in Q4. Finally, in the fourth quartile, companies with the highest Market Cap tend to have a longer Time to Completion, with a median slightly above 2, with greater variance than in the previous quartiles. This suggests that higher value transactions may take longer to complete for various reasons, such as the complexity of the transaction and higher costs. With respect to both Log Market Cap and Log Revenue, completion time tends to be longer for firms with higher values in the fourth quartiles, while firms with lower Market Cap and Revenue values tend to complete transactions more quickly. The distribution of Time to Completion is more varied in the higher quartiles (Q3 and Q4), indicating that operations with higher value companies are more complex and variable in terms of completion time.

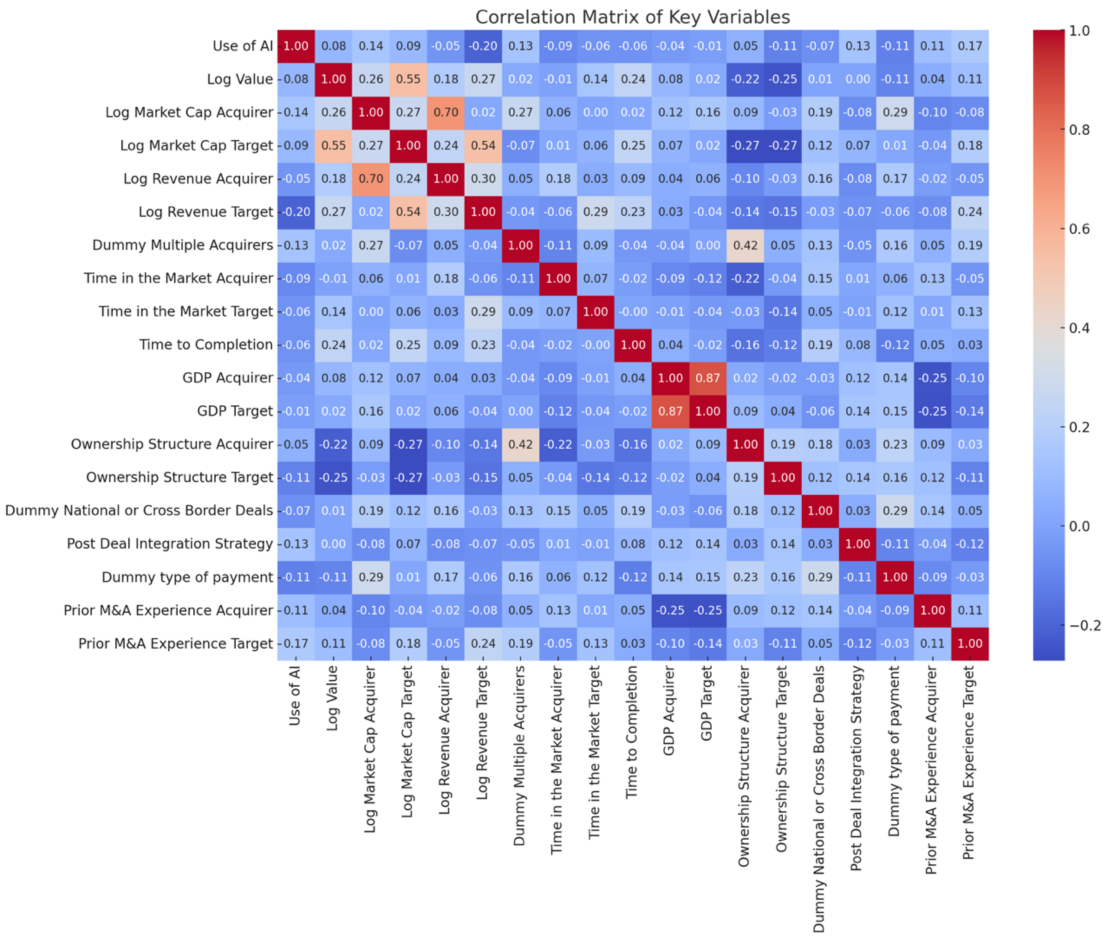
Chart 8: The relationship between Log Value and Log Market Cap Acquirer




Own calculations from sample data.

Here, the focus is on total value of the deal related to the Market Cap and the Revenues of both Acquirer and Target companies. Also here is presented just the case of the Log Market Cap of the Acquirer, to avoid redundancy. In the first quartiles there are trades made by lower market cap and revenue firms, and there is a tendency to have a lower log value so smaller transaction. In the fourth quartile with higher market cap acquirers the transactions tend to have higher trade values and grater variability, as evidenced by a wider distribution and some outliers. These two tables show that as the size of the firm increases, the complexity and the total amount of the operations increase, with a significant effect also in the time to completion.

Chart 9: The Correlation Matrix of key variables




Own calculations from sample data.

This matrix shows the correlation of the key variables used in the empirical analysis. The first variable that is interesting to analyze is Log Value, that is positively correlated with Log Market Cap and Log Revenues of the acquirer and target, which is to be expected, as company size affects deal value. It also shows a slight positive correlation with Time to Completion, suggesting that higher-value deals tend to take longer. Then Time to Completion shows signs of weakly correlation with Post Deal Integration Strategy, Ownership Structure Acquirer, and Ownership Structure Target, indicating that post-deal integration and ownership structure could influence time to completion. There is a slight positive correlation with Payments carried out by Stocks, confirming that deals paid with stock tend to take longer. The Use of AI variables is positively correlated with Log Value, Log Market Cap, and Log Revenue, indicating that AI is more frequently used in deals with higher-value companies. It does not show strong correlations with other variables such as Time to Completion or payment type. The variables of the ownership structure of both acquirer and target (the public or private state of the company) are weakly correlated with Time to Completion, suggesting that ownership structure only marginally affects completion times. Then we can see some correlation issue between the Log of the market cap and the Log of the revenue of the companies involved, this is because they are both indicators of the firm size ad characteristic so they can affect each other. This problem is also between the GDP of the target and the acquirer, because I reported just one GDP value for the acquirer on national deals and two distinct GDP in case of cross-border transactions. To avoid issues during the regression I duplicate the GDP of the acquirer on the GDP of the target, and this causes correlation. The correlation matrix confirms that variables such as Log Value, Market Cap, and Revenue are related to each other and to the Use of AI, while Time to Completion is only marginally influenced by factors such as payment type and ownership structure.

This analysis aimed to provide visualizations of key relationships between variables in the dataset, such as Time to Completion, Log Value, and other financial indicators.

### 2.3 Methodology and Data Cleaning

To study how AI could improve the M&A deal outcomes in this analysis the Ordinary Least Squares (OLS) regression is implemented as the initial technique to estimate the relationship between the Use of AI and the Time to Completion. This approach is appropriate for examining how AI impacts the duration of M&A deals because it allows us to identify general patterns and relationships between the independent variable (Use of AI) and the dependent variable (Time to Completion).

- $Time\ to\ Completioni = \alpha + \beta 1 \cdot Use\ of\ AIi + \gamma \cdot Xi + \varepsilon i$

Where, Time to Completion is the dependent variable, Use of AI is the key independent variable and (γ · X) represents a list of explanatory variables that are control variables to account for various factors influencing the time to completion of M&A deals, and finally ε is the error term. However, the OLS regression assumes that all explanatory variables are exogenous and if endogeneity issues arise, this model may produce biased estimates. If there is no significant endogeneity, OLS provides efficient estimates but given the complexity of M&A transactions, the model might fail to capture all the nuances, particularly if there are biases influencing both the deal value and the Time to Completion.

To address potential endogeneity concerns, Two-Stage Least Squares (2SLS) is employed as the more advanced econometric technique. Endogeneity can occur when the independent variable is correlated with the error term. In the case of this study, one source of endogeneity is the Log Value of the deal, which may influence the Time to Completion and, at the same time, could be affected by unobserved factors such as the complexity of the transaction or strategic motivations behind using AI. Using OLS without accounting for this endogeneity could lead to biased results.

The Instrumental Variable 2SLS (Two Stages Least Squares) model addresses this issue by instrumenting Log Value in a two-stage process:

1. The endogenous variable (Log Value) is regressed and predicted using the instruments and other exogenous variables. This generates fitted values for the Log Value, which are then used in the second stage.

$$log(Valuei) = \alpha + \beta 2 \cdot Use\ of\ AIi + \gamma 1 \cdot Zi + \varepsilon i$$

Where, (γ1 · Z) includes other instrumental variables and ε1 is the error term.

2. The predicted values of Log Value from the first stage are used as independent variables in the second stage regression to estimate their effect on the Time to Completion:

$$Time\ to\ Completioni = \alpha + \beta 3 \cdot log(Valuei) + \gamma 2 \cdot Xi + \varepsilon i$$

Where, 'Log Value estimated' is the predicted value from the first stage, ε2 is the error term in the second stage. Here, we evaluate the effect of Use of AI on Time to

Completion indirectly through the effect on Log Value, since AI was used as an instrument in the first stage of the regression.

Analyzing the complex M&A environment, it is likely that Log Value is endogenous to Time to Completion. In this case, endogeneity may result due to omitted variables, reverse causality or measurement errors, for example, because specific unobserved factors, not taken into account for lack of information, like managerial quality, specific industry condition or strategic motivation behind the operation, may influence both Log Value and Time to Completion (omitted variables); or because the Log Value could affect the choice to use AI, as firms might deploy AI tools to manage larger, more complex transactions, creating a feedback loop and thus the OLS estimator would become biased and inconsistent (reverse causality). Additionally, larger and more complex transactions (higher log value) may take longer to complete due to regulatory hurdles, post-deal integration difficulties given the deal complexity, or other strategic considerations. By instrumenting Log Value using valid instruments such as Use of AI, we can isolate the exogenous variation in Log Value and estimate a casual impact of Log Value on Time to Completion (unbiased estimate), correcting for endogeneity bias. The Use of AI is chosen as a valid instrument because it is likely correlated with the size and complexity of the deal but less likely to be directly correlated with unobserved factors that affect Time to Completion. The IV 2SLS regression provides a more robust estimation of the causal relationship between Log Value and Time to Completion than the OLS regression, which is critical for drawing conclusions on whether the use of AI in M&As contributes to more efficient transaction processes.

### 2.3.1 Data Cleaning

The data cleaning process is very important to conduct efficient regression analysis without including errors or data that are not easily readable and comparable by the software employed.

In my dataset on excel the first step was to transform the total deal value into billions instead of millions, this is because being a very heterogeneous sample once I looked for information regarding the size of the companies I realized a great variability, with companies going from values of a few tens of millions to companies such as Microsoft Corp, Alibaba Group or Berkshire Hathaway Inc with values of a hundred billion. Second, I transformed the deal value, market cap and revenue of the companies to a logarithmic scale, to address several issues in regression analysis, particularly: log transformation helps reduce the influence of outliers that are extreme values in the data. By compressing the range of these variables, log transformation ensures that excessively large or small values do not disproportionately affect the model's estimates, making the results more robust. Then, in many cases the relationship between the independent and dependent variables may be non-linear and the Log transformation helps linearize the relationship, allowing for a more accurate estimation of the effects in an OLS or other regression models. Finally, financial indicators like Market Cap and Revenue are often skewed, meaning their distributions are not symmetrical. Log transformation helps normalize the data by reducing skewness, making it more suitable for regression analysis where normally distributed variables are often an assumption. In particular, the formula for market cap and revenue was log(x+1), this is because all the data were in billions to consider the wide variety of information, but this way very small companies with lower values of market cap and revenues would have a transformed log value negative since the logarithm of a value under 1 (like 0.08 or 0.45) becomes negative. This would distort the information in my regression analysis, so by adding a small positive constant in all the variable data (log transformation with shift), we can avoid extremely low values and other problems. Then, an important control variable that could affect the Time to Completion of the deal was the type of payment of the transaction. In this case, the data download from the Bloomberg terminal had various classification: cash, stock, cash and stock, cash and debt. To avoid excessive complications in my analysis I turned the type of payment into a dummy variable with binary outcomes: 1 for payment made in cash (or mostly in cash, to include also cash and stock), 0 for payment made in stocks. Then, another dummy was added to study how the presence of multiple acquirers could influence the complexity of the deal, and it was 0 for one single acquirer buying a target and 1 for multiple acquirers (for example multiple private equity firms buying a strategic technological asset, or big infrastructure M&A with many stakeholders involved). Another important data about the data I collected, was the company age of the firms, when the deal was concluded. Even in this case a transformation in log helped the regression to include outliers without having to eliminate them. This information about experience is not the only one that can help us understand how the longevity and the familiarity with these deals can affect the duration of a transaction. Prior M&A experience is another binary variable with 1 if the acquirer or the target had some experience (at least one) in this field, and 0 otherwise. Then a big work of classification was needed to divide 140 deals (so 280) companies from a very wide range of industries and sub industries. This is the result of industry groupings for Reclassification:

1. Technology: Includes Technology and Software, Information Technology (IT) Services, Telecommunications, Semiconductors Industry, Cybersecurity, Mobile Gaming, Gaming Development, Network Video Solutions, Software and Industrial Design, and Digital Advertising, Security Products, IT Outsourcing & Business Process Outsourcing (BPO), Semiconductor and Electronics Manufacturing, Imaging and Optical Products, Network Video Solutions.
2. Financials: Includes Banking, Insurance, Private Equity, Investment Management, Mortgage Servicing, Business Development Company (BDC), Real Estate, and other Financial Services, Banking and Financial Services, Life Insurance, Claims Management, Business Development Company (BDC), Retail and Commercial Banking, Trading and Investment.
3. Energy: Includes Oil & Gas Exploration and Production, Renewable Energy, Natural Gas Distribution, Electricity, and other Energy Sector-related activities, Energy Sector.
4. Healthcare: Includes Pharmaceuticals, Biotechnology, Healthcare Services, Medical Devices, and Life Sciences, Biotechnology & Pharmaceuticals.
5. Consumer Staples: Includes Food and Beverage, Tobacco, Cosmetics, Personal Care Products, and other industries related to Consumer Essentials, Tobacco Products, Cannabis Industry, Consumer goods (chemicals, personal care).
6. Consumer Discretionary: Includes Automotive, Home Appliances, Retail, Media, Entertainment, and other Discretionary Consumer Goods and Services, Retail and Consumer Goods, Gaming and Entertainment, Home Appliances and Consumer Electronics, Automotive & Powertrain Technology, Broadcast Television.

7. Industrials: Includes Manufacturing, Engineering, Construction, Transportation, Aviation, Infrastructure, and Support Services, Manufacturing (automotive and aerospace sectors), Airline, Construction, Infrastructure, Engineering and Support Services, Building Materials & Construction Supply, Building Materials and Construction Aggregates, Portable Storage Solutions (providing secure storage containers and mobile offices to industries such as construction, retail, and manufacturing), Aerospace and Defense Engineering, Infrastructure Investment, Shipping and Gas Transportation, Engineering and advanced manufacturing (automotive and aerospace sectors), Diversified Conglomerate (with interests including infrastructure, energy, and resources), Infrastructure/Transportation, Ports and Logistics.
8. Materials: Includes Chemicals, Plastics, Mining, Agriculture, Cement and Building Materials, and other Material Production Sectors, Steel Production and Mining Industry, Chemicals and Plastics, Fertilizer and Chemicals Industry, Agribusiness, Materials trading, Environmental Protection, Steel production and mining industry, Mining (Gold), Biotechnology/Agri-food, Agribusiness, Cement and Building Materials, Chemicals and Plastics, Paper and Packaging.
9. Telecommunications: Specifically includes Telecommunications Services and Telecom Infrastructure.
10. Utilities: Includes Electricity, Gas Transmission, Water Utilities, and Renewable Energy, Utilities (Electricity and Gas Transmission), Renewable Energy, Natural Gas Distribution and Transmission.

Unfortunately, with all the others key explanatory variables it made no sense to create ten different binary variables to study the behavior of AI in all these industries, so this simplification needed major condensation. At first, I assigned a number 1 to 10 to each one and use this information as a categorical variable but, doing so, the difference between every industry in the regression was considered as 1 (from 2-financials to 3-energy) and this biased my results. Then I decided to focus on the most important ones for my goals, and I created three variables: D_TET composed by the industries on technology, energy and telecommunications, D_Fin where every financial firm was included and Others with the rest of the data. These variables added complexity to the model since they were still dived between acquirer and target, making six more explanatory variables summing to the list. Finally, the solution was considering just the acquiring companies (since the majority of M&As was in the same industry, with few exceptions) and accounting for just D_T including technological companies and D_Fin with the financial services industry.

The enormous variety of the deal included in the sample, was confirmed also by the data about the geographic location of the deals. Since the inclusion country by country in the regression would lead to a waste of time because of the complexity of the data already present in the model, I divided the sample into national or cross-border deals, to study if the M&A transaction would have suffered an increase of time for international or foreign deals. The 40.71% of the transaction included are cross-border deals, and this becalmed a dummy variable with binary outcome: 0 for national M&As, 1 for cross-borders operations. Then there was the fundamental Time to Completion variable, calculated in days. Since this solution brought to larger coefficient more uncertain to interpret, we decided to simply divide the data by 100 to make data easily readable. To study a complex deal like this is important to account also for the economic conditions in which the deal was made. For this reason, I included also the value of the GDP of the acquirer and the target countries. Since most deals was within the national borders, a lot of values of the GDP between the acquirer and the target were similar, causing problems of correlation in the regression's outcome. The solution here was to account just for the GDP of the acquirer, without adding another variable that, as we seen in the Chart 4, has almost zero effect on the M&A duration alone. Another important distinction must be made considering the ownership of the companies, dividing into a dummy variable with 0 for public firms and 1 for private ones. Most of the information were founded in the companies' financial reports but data about private companies were much more difficult to find. The last variable transformed in 0 or 1 was post-deal integration strategy, but this data was not very useful since within 140 deals only 6 was publicly declared failed.

### 2.4 Explanatory Variables

The Table 4 with all the explanatory variables can be found at the Appendix 1. The interaction variables between AI and relevant control variables or GDP and the dummy national or cross-border deals, try to examine how the effect of one variable, such as the Use of AI, depends on the level of another variable (Log Market Cap, GDP, Type of Payment, Prior M&A experience, Industry). They help capture the conditional relationships between variables, showing how the influence of AI on outcomes like Time to Completion or Log Value may vary depending on contextual factors such as the payment method, market environment, or industry sector.

These variables have a wide range of sources: Bloomberg, Financial Times, S&P500, SEC government website, Market Screener, Merg, Stock Analysis. Most of the available data, however, comes from company websites and reports.

**2.5 Econometric Models**

The goal of my empirical analysis is to demonstrate the positive impact of the introduction on AI technologies to improve and streamline the M&A process. To do so with real data it is normal that the model requires an iterative process of improvement, adding or subtracting new variables or transforming existing ones. The key is to find a set of independent variables that better explains the dependent variable, Time to Completion. I started this process by adding as many variables as possible to complicate the OLS regression model and to understand the relationship between the explanatory variables with the dependent one, and then proceed simplifying further and further to obtain a strong and valid output to interpret. This model was just a starting point to estimate the relationship between the Use of AI and the Time to Completion. Since this is an OLS, there are some assumptions about no endogeneity among the explanatory variables and that the errors are homoscedastic. Alongside the independent variables, there are several control variables like Log Market Cap, Log Revenue, Dummy type of payment, Dummy National or Cross Border Deals and so on. Throughout the development of the OLS model, we performed several diagnostic tests to ensure the validity of the results. First, we examined multicollinearity using the Variance Inflation Factor (VIF). While most variables showed low VIF values, indicating acceptable levels of multicollinearity, certain variables like Log Market Cap and Log Revenue initially displayed high VIF scores, also with all the control variables present in the regression, there was a lot of correlation problems with the interaction variables and, for example, between GDP Acquirer and GDP Target, leading to the decision to drop one of them. To resolve this, we log-transformed the variables and simplified the model by removing redundant interaction terms, mostly between AI and type of payment or AI and the ownership structure of the acquirer or target, and this significantly improved the multicollinearity issues. The next step was to check also a correlation matrix considering all the independent variables, and this evidenced problems between the interaction variables between AI and Prior M&A Experience of the Acquirer, which results basically the same information between the two. We also performed all the test to control for the heteroscedasticity of the error terms, like the Breusch-Pagan test and the White test. The results do not show relevant problems of heteroscedasticity but upon identifying heteroscedasticity in the model, we applied robust standard errors to correct for this issue, ensuring that the coefficient estimates remained unbiased and consistent. Even though some variables have not yet shown significance, the model has improved, and the reason behind this problem may be due to the small sample size. To improve the consistency of the results, we perform the same exact regression also with the log form of Time to Completion that do not change the purpose of the analysis but what changes is the interpretation of the results.

To study also how AI affect the cost efficiency of the M&A deals, we study also another dependent variable, that might be related to the complexity of the deal, causing longer completion time and so higher costs for the companies. The 2SLS model extend the OLS regression by analyzing if the Log Value could be correlated with unobserved factors (like regulatory hurdles or the management of the firm), affecting both the deal size and Time to Completion, leading to biased estimates. To address this, we instrumented Log Value using variables such as Time in the Market Acquirer and Use of AI between the others (which served as exogenous controls), which were strongly correlated with Log Value but not directly with the error term in the second-stage regression. It was fundamental to do not comprehend Time to Completion between the exogenous variables in the first stage, to avoid identification problems. In the second stage, the predicted values of Log Value from the first stage were used in the main regression equation to estimate their effect on Time to Completion. This two-step process allowed us to account for endogeneity and provided more robust estimates of the effect of AI on M&A efficiency. Additionally, as before we confirmed the validity of our instruments using instrument relevance tests to ensure that the instruments were strongly correlated with the endogenous variables.

The results in both models were thoroughly examined to ensure their robustness, and all diagnostic tests supported the reliability of the estimates. Now is possible to present the output from these models.

**2.6 Results (Output)**

The first final OLS regression has always Time to Completion as dependent variable, Use of AI as the key independent variable, and then multiple control variables such as Log Value, Dummy type of payment, Log Market Cap Acquirer, D_T, Prior M&A Experience Target, Dummy National or Cross Border Deals, Ownership structure Acquirer and three interaction variables to study the behavior of some characteristics influenced by the Use of AI.

The results of the OLS regression model are presented in Table 5. The model had been further implemented applying heteroscedasticity-robust standard errors that assumes unequal variance across residuals, to account for potential issues with heteroscedasticity. As we can see from the R squared, the model explains approximately 20.3% of the variance in the time to completion, with an adjusted R squared of 0.127, adjusted for the number of predictors in the model, indicating a moderate level of explanatory power. The degrees of freedom are 127 for residuals and 12 for the model, this give an idea of how many predictors were used and how much freedom remains for estimating the error. The F-statistic, not showed in the Table, is significant indicating that the model provides a statistically significant fit. After the iterative process to choose the best explanatory variables that can affect the duration of an M&A deal with real world data, several key variables were found to impact significantly the Time to Completion. Even if just the 28% of the sample integrated the Use of AI systems during the M&A, the regression shows interesting results, since the Use of AI in these transactions is associated with a significant reduction in the time to completion ($\beta = -1.483$, $p = 0.002$), suggesting that AI adoption accelerates deal closures.

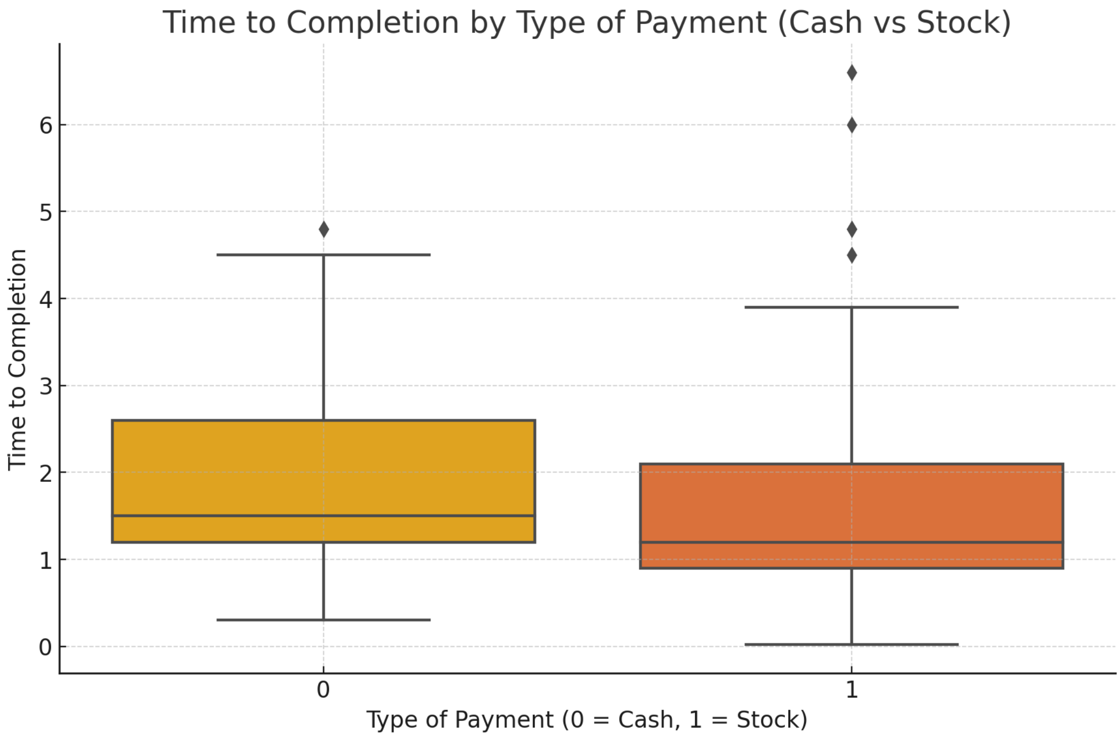
Table 5: OLS regression of Time to Completion

| **OLS regression results** | **Dependent Variable: Time to Completion** | |
|---|---|---|
| **Variables** | **Coefficient** | **Standard errors** |
| Use of AI | -1.4833** | (0.471) |
| Log Value | 0.4222** | (0.137) |
| Dummy type of payment | -0.8355** | (0.310) |
| Log Market Cap Acquirer | -0.0698 | (0.101) |
| Log Revenue Acquirer | 0.0572 | (0.105) |
| D_T | -0.5330* | (0.237) |
| Prior M&A Experience Target | -0.1979 | (0.223) |
| Dummy National or Cross Border Deals | 0.6324** | (0.218) |
| Ownership structure Acquirer | -0.3421 | (0.244) |
| Interaction_AI_Type_of_Payment | 1.0341** | (0.409) |
| Interaction_AI_Prior_MA_Target | 0.6105 | (0.409) |
| Interaction_AI_D_T | 1.1814 | (0.880) |
| Const | 1.8849*** | (0.332) |
| No. Observations | 140 | |
| R – sq | 0.203 | |
| Adj. R – sq | 0.127 | |
| p-values in parentheses<br>* p<0.05, ** p<0.01, *** p<0.001 | | |

Regression results computed using sample data and Python.

This indicates that AI significantly reduces the dependent variable by approximately 148 days, considering the transformation of Time to Completion to clear the data, suggesting that AI technologies streamline the process, making deals faster to complete. Similarly, the type of payment used also has an impact on completion time, with deals involving certain payment types experiencing a significant decrease in the dependent variable. This variable is fundamental in M&A transactions, because it directly influences the complexity and duration of the deal-making process. About this we can make some considerations: first, stock-for-stock transactions tend to be more complex compared to cash transaction, and this is interesting to compare with a chart from the cleaned excel data between the relationship of duration of the deal and type of payment.

Chart 10: The relationship between Time to Completion and Type of payment




Own calculations from sample data.

While the comparison between Time to Completion and Type of payment give this result, showing shorter duration of the deal for stock transactions, the regression in which we consider all the explanatory variables effects together showed the opposite outcome. This is because in stock deals, both parties need to agree on the relative value of the acquirer's stock and compare it to the target company's value and this means detailed negotiation or analysis of market conditions that can lengthen the time to reach an agreement, affecting Time to Completion. The unreliable result from the cleaned excel file, is probably biased because of the small size of the sample and so it might be a random result since there is not enough statistical significance with such small observations. On the other hand, cash deals are often simpler as the acquirer pays a fixed amount upfront. This is confirmed by the OLS regression where the cash payments significantly reduce Time to Completion. Other main reasons behind this information could be because stock transactions require more regulatory attention or approval from shareholders (especially in listed companies), market conditions also could affect the choice between cash and stock when stock prices are high because companies might prefer stock deals that requires longer times to assess the risk of future fluctuations; financial availability of cash also potentially affect this choice since cash payments require liquid assets.

Then the regression shows that the logarithm of the deal value significantly increases the Time to completion, implying that larger deals ted to be more complex and take longer to finalize. Generally, this is true because larger deals tend to involve more complex negotiations, due diligence processes, and more stringent regulations which can increase the time needed to conclude the transaction. Here, the transformation of the variable with the logarithm allows to normalize extreme values, making it easier to capture proportional differences and interpret the marginal impact of changes in deal value on the time to completion, thus providing a clearer picture of the relationship with y. Higher-value deals, might also attract more resources and dedicated teams, potentially speeding up certain aspects of the process, while at the same time facing more stakeholder involvement, which can prolong the deal. Moreover, regulatory approval is more rigorous for larger deals, and combined with complex financial and strategic assessment, slow down the process, adding further delays. Incorporating deal value in logarithmic form into the model allows us to explore how deal size influences the speed of completion, capturing the non-linear relationship between the two variables. The size of the deal is often a proxy for the level of risk involved in a transaction, so the acquiring firms may take longer to evaluate the risk, making them more cautious during discussions with the target, with the due diligence, and closing.

The other independent variable that was expected to reduce Time to Completion other than the AI impact, was D_T representing companies in the technology sector. The coefficient of D_T suggests that technology companies, on average, experience a shorter time to complete M&A deals, with a reduction of 0.53 in Time to Completion.

This effect is significant, considering that is approximately one-third of the reduction in Time to Completion produced using AI. This result is consistent with the idea that companies in the technology sector may benefit from a more agile and streamlined M&A process since they are the first ones to invest and develop these systems. Several factors may explain this phenomenon. First, technology firms tend to have more efficient due diligence process, because of the standardized and digitalized operations in which they operate. Additionally, the technology sector often includes companies that are more familiar with rapid innovation and may have more adaptable corporate structures. These characteristics can facilitate faster decision-making, integration, and execution of M&A deals. Moreover, technology companies might also be at the forefront of adopting digital tools and AI-driven processes, even if they are not explicitly categorized under the Use of AI variable, also considering the difficulty to obtain information about the integration of AI in M&A from non-listed firms.

Another fundamental explanatory variable is the Dummy of National or Cross-Border Deals. This variable also experiences longer Time to Completion, and this could be because of several factors. Indeed, cross-border transactions introduce complexities that can significantly influence the duration of the deal process. If we consider cross-border M&As, the complexity of deal significantly rise because of differences in legal frameworks, regulatory requirements, cultural dynamics, and market environments between countries, that can lead to longer negotiations and due diligence procedures. Let's imagine for example that there are a lot of cultural differences between the two companies, that comes from two very different part of the world. Considering just the language barriers or the different regulatory framework of the countries with different standard contracts, the deal could be extended for months. These factors often add layers of complexity compared to domestic deals, where acquirers and targets operate within the same legal and economic environment. During cross-border deals instead, may require navigating foreign regulatory bodies and approvals, which can delay deal finalization. Differences in corporate governance standards like accounting practices or tax regimes may introduce additional due diligence requirements, increasing Time to Completion. National deals have fewer barriers to regulatory compliance leading to faster integration processes. These differences show us how the international dimension of M&A influences operational timelines, considering that technology is still a new in these environments and that much of the underdeveloped countries do not have these resources. This insight is crucial for firms aiming to optimize the efficiency of their acquisition strategies in different geographical contexts. These considerations provide valuable empirical evidence for who practice this profession and academics that might study ethical M&A takeovers in underdeveloped countries, focusing on M&A deal dynamics.

The last explanatory variables that show significance in the OLS model is the interaction between the Use of AI and the Type of payment. This suggests that in certain conditions, the combination of AI systems and specific payment methods may lead to longer Time to Completion, possibly due to complexities in implementation or integration. Both AI and the type of payment (cash or stock) are binary variables that reflect distinct dimensions of the deal process: one related to technological efficiency and the other to the financial structure of the transaction. AI reduces the time needed to perform tasks such as due diligence, risk assessment, contract analysis to streamline the M&A process, while the type of payment can introduce complexities as we have seen before. Studying the interaction between these two variables allows us to assess whether the use of AI accelerates Time to Completion of the deal more in cash-based transactions, where efficiency gains might be more readily realized, or in stock-based deals, where the potential for delays could be mitigated by AI's automation and analytical capabilities. This interaction effect is particularly important because it admit that the impact of AI may not be uniform across different financial structures and may provide nuanced insights into where AI can deliver the most significant time savings in M&A processes. Indeed, it might seem counterintuitive if their interaction results in a prolongation of the dependent variable. However, this could happen for several reasons related to how interaction effects work in regression models. The interaction term captures the combined effect of two variables beyond their individual impacts, so if the interaction coefficient is positive, this suggests us that when both AI and a type of payment are present together, the effect on Time to Completion is different from the sum of their individual effects. Despite both binary variables reducing the y when considered separately, the positive interaction might indicate that combining AI with a certain type of payment (likely stock) introduces new complexities or inefficiencies that counterbalance the individual benefits. The benefits of AI might be less effective in speeding up the deal in a stock-based deal because these operations can involve intricate valuation processes that AI can't fully mitigate. The interaction term thus reflects the complexities introduced when these two time-saving factors overlap, leading to new challenges not present when these variables act independently.

While some variables, have been included for potential effects on the dependent variable they did not show statistically significance. The logarithm of the Market Cap and the Revenue of the acquirer, Prior M&A experience of the target, and Ownership structure of the acquirer had a p-value greater than the significance level, so we cannot confirm that there is a significant relationship and a significant impact between the independent and the dependent variables.

Other indicators in the regression's output are the model diagnostics, which indicate a relatively well-fitting model, though the Jarque-Bera test, the Durbin-Watson statistic that suggests no significant autocorrelation in the residuals, and the low condition number of 39, that does not indicate multicollinearity concerns.

Furthermore, an additional OLS regression was prepared with the logarithm of Time to Completion as the dependent variable. Since it leads to very similar conclusions, it is not very useful to analyze this model individually, but it would be interesting to interpret the indirect effect of the explanatory variables on the dependent variable, transformed by the logarithm.

Table 6: IV 2SLS Regression

| **IV2SLS Regression Results** | **Dependent Variable: Time to Completion** | |
|---|---|---|
| **Variables** | **Coefficient** | **Standard errors** |
| Use of AI | -0.8659* | (0.406) |
| Dummy type of payment | -1.3216 | (0.788) |
| Dummy National or Cross Border Deals | 0.8814* | (0.413) |
| Log Value_predicted_final | 0.6370* | (0.271) |
| Const | 1.5608* | (0.653) |
| No. Observations | 140 | |
| R - sq | 0.172 | |
| Adj. R – sq | 0.111 | |
| p-values in parentheses<br>* p<0.05, ** p<0.01, *** p<0.001 | | |

Regression results computed using sample data and Python.

The IV 2SLS regression output provides valuable insights into the relationship between the use of AI and deal characteristics on the duration of M&A transactions. To prove that the Use of AI has a significant and relevant impact it is not enough to demonstrate that it can reduce the duration of the deal, it is important to proceed one step forward. This model allows us to make some more considerations about the effects of the use of AI in the M&A environment, because we do not study directly the influence of the numerous variables on Time to Completion, instead, we focus on the determinants of the Log Value first, which is an indicator also for the complexity and therefore for cost efficiency of a deal. To reach the aim of this work, the idea was to perform other regressions on different dependent variables such as Cost Efficiency, but with the lack of information of non-listed companies and the poor availability of data combined with the enormous number of factors that we must consider (and have access to it) to perform these new models it was not possible. The idea of using a proxy instead was useful but given that there is no scientific basis for something like cost efficiency in the literature of M&A it was not possible to include. Hence, we introduced the 2SLS to analyze the effect of the use of AI on both Log Value and Time to Completion together.

The 2SLS regression model presents key statistical features that support the robustness of the analysis. The R-squared value of 0.172 indicates that the model explains 17.2% of the variance in Time to Completion, which is relatively low but, considering that this empirical analysis is based on real world data of a complex phenomenon like M&A, can be considered a good explanation. The adjusted R-squared slightly lowers the explanatory power to 11.1%, accounting for the number of predictors included. The F-statistic and its corresponding p-value confirm the overall significance of the model, indicating that the independent variables collectively provide meaningful insight into the dependent variable.

In the first stage of the regression Log Value was instrumented using the following variables: Use of AI, Log Time in the Market (Acquirer), Log Time in the Market (Target), Log Market Cap (Acquirer), Log Market Cap (Target), Log Revenue (Acquirer), Log Revenue (Target), and Dummy National or Cross Border Deals. The purpose of this stage was to estimate Log Value based on factors that could influence deal size while addressing potential endogeneity concerns between Log Value and Time to Completion. In this regression, variables that were not taken into account because not relevant for the valuation of the effects on Time to Completion has been introduced. For example, the company age that resulted a redundant information studying the duration of the transaction, becomes a fundamental aspect to consider the total value of the M&A. Other deal characteristics like the revenues and the market cap of both acquirer and target, together with the dummy for national or cross border deals had a non-negligible effect.

The second stage regression used the predicted Log Value from the first stage to assess its impact on Time to Completion, alongside other explanatory variables, such as Use of AI and Dummy Type of Payment. The model controls for deal-specific factors and adjusts for potential endogeneity in the relationship between deal value and time to completion. Here we can see how both Log Value and Use of AI affect the duration of the M&As.

The most important coefficient, the one for Use of AI is both negative and statistically significant at the 5% level. This implies that the adoption of AI in M&A processes reduces the Time to Completion, so deals with companies implementing AI systems complete approximately 0.87 units of time faster than those that do not, all else being equal (consider always the transformation: Time to completion/100). This finding strongly supports the hypothesis that AI improves the efficiency of M&A transactions by streamlining decision-making, due diligence, and other critical processes, but this finding alone is not enough. The statistical significance of the result highlights the robustness of this effect.

To highlight the impact of the introduction of AI technologies and assess that not only they affect the duration of the deal, but also the complexity and therefore the cost efficiency of the M&A, we might interpret the endogenous variable Log_Value_predicted_final. The predicted Log Value from the first stage of the 2SLS model has a positive and significant coefficient (0.6370, p=0.023). This result indicates that higher deal values, as predicted from the instrumental variables, are associated with longer Time to Completion. This makes intuitive sense, as larger deals typically involve more complexity, scrutiny, and regulatory oversight, leading to extended timelines. However, even though larger deals take longer to complete, the use of AI can still reduce this time, as evidenced by the negative coefficient for the Use of AI variable.

The Dummy Type of Payment variable, although shows a negative coefficient (suggesting that deals involving a certain payment type, cash or stock-based transactions, tend to complete more quickly), is not statistically significant at the 5%, so we cannot interpret since it does not have a reliable effect on the dependent variable. The direction of the coefficient may provide some insight into deal dynamics, even though the effect is not as strong as other variables in the model.

Finally, the Dummy National or Cross Border Deals variable is positive and significant, even more than the Log Value predicted in the first stage, indicating that cross-border deals tend to take longer to complete compared to domestic ones. This aligns with expectations, as we saw before, cross-border transactions involve more regulatory complexity and cultural differences that contribute to longer completion times.

The tests included in the regression output, such as the Omnibus (2.370) and Jarque-Bera (JB = 2.121, p = 0.346) for the normality of residuals, suggest that the residuals are normally distributed, which supports the assumption of normality crucial for both OLS and 2SLS models. Additionally, the Durbin-Watson statistic (1.852) suggests there is no autocorrelation in the residuals, reinforcing the reliability of the model. Metrics related to the distribution of residuals, such as Skew (0.361) and Kurtosis (2.416), indicate that the residuals are approximately symmetrically distributed and close to normal, which aligns with the assumptions of linear regression models. Finally, the Condition Number (8.20) suggests no multicollinearity issues among the independent variables, ensuring that the estimates are not distorted by multicollinearity. The statistical properties of this model are that there are normal residual distribution, lack of autocorrelation, and low multicollinearity, which contributes to increase the validity and the robustness of the 2SLS approach in exploring the relationship between AI usage, Log Value, and Time to Completion.

The findings from the 2SLS model are essential in supporting the central argument that AI can boost M&A transaction efficiency. The notable negative correlation between AI and Time to Completion indicates that implementing AI can expedite the M&A process, reducing the duration needed to conclude deals. This means to represents a contribution to the current gap in the research, which has typically concentrated on AI's influence in particular phases, such as due diligence, without thoroughly investigating its impact on overall transaction timelines.

Furthermore, the use of a 2SLS approach in the analysis tackles potential endogeneity issues. Log Value is used as an instrument to account for the possibility that Time to Completion might affect deal value, rather than the other way around. The significant coefficient for Log Value predicted shows that larger transactions require more time, while also validating Log Value's use as an instrumental variable in this scenario. This 2SLS model offers evidence checking the hypothesis that AI can enhance M&A efficiency by decreasing Time to Completion. The model also emphasizes how deal value and cross-border factors influence transaction durations. These discoveries underscore AI's potential to streamline complex, high-value transactions, ultimately contributing to a more efficient M&A process overall.

**Conclusion**

The analysis conducted in this chapter provide key insights into the role of artificial intelligence in optimizing the efficiency of M&A processes. Using both OLS and 2SLS regression models, we evaluated the impact of various factors on Time to Completion and deal value, with a particular focus on the use of AI. The findings consistently highlight that AI has a significant negative effect on Time to Completion, indicating that AI usage reduces the time needed to finalize M&A deals. This suggests that AI is an important tool for streamlining deal processes, especially in the areas of risk management and decision-making.

Moreover, the inclusion of Log Value as an instrumental variable in the 2SLS model allowed us to address potential endogeneity issues and provided a deeper understanding of how AI impacts both deal value and the Time to Completion. The 2SLS analysis confirmed that AI also positively affects Log Value, confirming that companies that integrate AI systems not only complete deals more efficiently but also achieve higher deal values.

However, there are several limitations in study caused by two key factors. The most important one is the relatively small sample size, comprising only 140 observations and data about more than 280 companies (without considering multiple acquirers deal). Even if this could be a good starting point to make some consideration about M&As, these operations are too complex to be defined and tracked down with so little information. That is why it was very important to expand the heterogeneity of the sample, to capture as much variety and randomness as possible. The second problem with having few observations is that this could lead to bias assumptions. One clear example is the type of payment we considered in the first OLS regression. This variable, confronted directly with the time to completion presented a reduction on the duration of the transactions for stock payments deals. Ones it becomes one of the multiple explanatory variables in the regression model, his effect on Time to Completion was the exact opposite, with the cash payment simplifying and speeding up the M&As. This constraint of a small sample size may affect the generalizability of the results and leaves room for potential biases like this one we just saw or unexplored variations in the data. Additionally, while our model addressed potential endogeneity concerns, there could be other unobserved variables that influence both deal value and Time to Completion, like the management of the companies.

To further improve these findings, Chapter III will employ Monte Carlo simulations, which will allow us to generate a larger dataset duplicating the real-world dataset, to provide a more robust scientific basis for the conclusions drawn in this analysis. The simulation will also help explore scenarios that were not possible to test due to the limited sample size.

Finally, the results offer valuable insights for M&A practitioners since from a practical point of view, firms can leverage AI to enhance not only the speed of deal processes but also the quality and value of outcomes. As AI technology continues to advance, its integration into M&A processes is likely to become even more critical. Future research should explore these dynamics over a longer period and with larger datasets to validate the role of AI in enhancing deal efficiency and performance. Companies that aim to remain competitive in the M&A environment should consider investing in AI technologies to optimize their deal processes and enhance decision-making capabilities, leading to more successful and efficient transactions.

# CHAPTER III
# MONTE CARLO SIMULATION

## Introduction

This chapter aims to address the main limitation of the regression analysis conducted with real data in Chapter Two, namely the small simple size of 140 observations due to the concentration on M&A cases in recent years. To address this problem, we employed the Monte Carlo simulation technique, duplicating data and introducing simulated variations. This approach allowed us to create "twin" companies based on real-world M&A data. With the previous analysis, I had no alternative, I had a limited amount of information about the companies photographed in that precise state, but the duplicated datasets allow me to introduce slight variations (noise) on the distributions, enabling me to observe the potential impact of changes in key variables, such as the Use of AI, without altering the central structure of the estimated parameters.

After applying the Monte Carlo method to generate a sufficiently large data sample, two separate OLS regressions were performed in which small changes were introduced regarding our variable of interest, Use of AI, to estimate the effect on Time to Completion as previously done, but this time on a statistically significant sample. The twin data generated on the companies were used to examine the impact of changing one variable while holding all other parameters constant, to avoid affecting the variability and distribution of the real data.

This process allows us to reinforce the validity of the results of the previous analysis, which was hardly generalizable by working with just a few observations. It also allows us to explore hypothetical scenarios, such as the adoption of AI sourced from a normal distribution or the study of many new companies in technology and finance adopting AI, could affect the Time to Completion. Although not all data now come from real companies, introducing noise into the twin dataset simulates real-world uncertainty, ensuring that simulation results better reflect the variability found in real M&A processes.

### 3.1 Literature review

The past research that will be mainly taken as reference is that of Netter et al. (2011), Shu-zhi et al. (2010) and Alimhamzah et al. (2022).

The research conducted by Netter et al. shows the importance of constructing a large and heterogeneous sample size to perform consistent analysis of the M&A environment. In fact, by analyzing over 300,000 deals, the authors highlight how typical screens in M&A studies, like focusing the research on a limited number of listed companies excluding non-listed firms, can drastically reduce sample sizes and skew the results. This is because private acquirers represent a significant portion of M&A activity, and by excluding them the research led to incomplete or biased findings. These findings are particularly important for my thesis and the assumptions on which it is based. For this reason, even though the sample was limited to 140 observations, it was made highly heterogeneous to include and represent the variety and randomness of the real world, and to avoid typical biases (such as excluding smaller deals or focusing on a precise geographical area). This consideration emphasizes the importance of this chapter, because despite starting with a limited sample, the Monte Carlo method allows for a substantial expansion of the number of observations, thereby increasing the statistical significance of the results obtained and a robust empirical analysis. Shu-zhi et al. explored the use of Monte Carlo Simulation combined with the Crystal Ball tool to improve decision-making in M&A processes. This paper critiques the traditional discounted cash flow (DCF) model and highlights its failure to account for managerial flexibility and uncertainty, suggesting the use of real option analysis (ROA) and Monte Carlo simulation to better manage the risks in the uncertain environment of M&A transactions. Here, Monte Carlo simulation is implemented with both DCF and ROA to simulate multiple outcomes based on volatility and uncertainties in the market. The article becomes relevant to this research since it uses the same tool, Monte Carlo Simulation, for empirical analysis to study M&A decisions, but with different purposes. The research from Alimhamzah et al. uses the Monte Carlo method to evaluate the financial performance of a new share acquisition, generating multiple possible outcomes for cash flows, synergies, and exit multiples in the Indonesian telecommunications sector. The paper also employs discounted cash flow (DCF) analysis and financial statement modeling. This research is relevant in our context due to its approach, using Monte Carlo Simulation to estimate M&A outcomes, just like the purpose of this chapter. Although its focus on a new share acquisition case is not directly linked with the specific analysis of the introduction of AI in M&A processes, it still offers insights into how Monte Carlo simulations can be applied to assess financial risks.

### 3.2 Econometric Models

Data constraints, regarding the number of observations in the sample presented in the second chapter, limited the robustness of the econometric models. The handling of this problem was solved by applying the Monte Carlo method on this data to enlarge the sample. The core idea behind this technique is to test how changes in specific assumptions, such as the assumptions of AI adoption, affect the outcomes observed in previous models. The goal was to generate a larger dataset through the creation of "twin" companies from the real data collected to simulate M&A scenarios perturbing some variables. This method introduces controlled noise and variability, ensuring that the dataset reflects the inherent randomness and heterogeneity of real-world market conditions. The expanded dataset was used to run two distinct OLS regressions, where I altered one key assumption at a time, while keeping all other variables and parameters constant.

In the first regression the idea was to stochastically expand the sample with Monte Carlo, by varying variables that are more or less fixed or with few observations, through the modification on the assumptions on Use of AI, to see how the result changes. To do this I calculated the average Use of AI 27,86 % and its variance 44,99% from the original dataset and substitute them with random drawings from a normal distribution to generate new data. Then I included this new variable in the dataset, substituting the binary Use of AI. Afterwards, I duplicated this data with the other explanatory variables using Monte Carlo Simulation, generating 1000 simulations for each deal. The aim of this regression was to answer this simple question: what level of AI guarantees me a reduction in Time to Completion of 20%? For this purpose, I ran this regression with a target of 20% reduction in Time to Completion by multiplying the new AI variable by a 'reduction factor' calculated as: $\text{reduction}_{\text{factor}} = 1 - \left(\text{ai}_{\text{use}} \times \left(1 - \text{reduction}_{\text{target}}\right)\right)$ The second OLS regression still analyzes the effect of AI use on the duration of the deal, but with different adjustments. The only modification here was about the industry of the companies: new firms from the technology and financial sectors generated by simulation are more likely to use AI, while other sectors have less chance. If the generated company belonged to the technology or financial services sector it would have an 80 percent chance of using AI, while if it belonged to the other sectors only 20 percent. The results of these simulations will be presented in the following section.

### 3.3 Results (Output)

In the first model, with the modification on the Use of AI variable we have some interesting results, shown in Table 7. The R-squared of 19.6% indicates a moderate fit for this model, only a fifth of the variation in the dependent variable is explained by this model. This R-squared value may seem low compared to real data models; however, in the context of a Monte Carlo simulation, it is not necessarily a poor result. Monte Carlo simulations often introduce variability that captures a wide range of possible outcomes, making it difficult for any model to explain a very high percentage of variance, so a 19.6% R-squared is indicative of the complexity of the M&A processes being modeled, especially considering that the goal is to test how various variables interact under simulated conditions. The new variable created with random drawing from a normal distribution is negative and statistically significant showing that an increase in the integration of AI is associated with a reduction in the time required to complete an M&A. Since these data comes from a large sample size of 140,000 observations, they all have large t-value and low p-value, suggesting that their effect on the dependent variable is also highly reliable. This result supports the hypothesis that AI can enhance deal efficiency by speeding up processes like due diligence and decision-making.

Table 7: OLS Regression by Monte Carlo Simulation with AI normally distributed

| OLS regression results with Monte Carlo Simulation | Dependent Variable: Time to Completion | |
|---|---|---|
| **Variables** | **Coefficient** | **Standard errors** |
| AI | -0.3782*** | (0.003) |
| Log Value | 0.1791*** | (0.002) |
| GDP Acquirer | 4.0021*** | (0.083) |
| GDP Target | -2.2472*** | (0.069) |
| Ownership structure Acquirer | -0.2871*** | (0.003) |
| Ownership structure Target | -0.0831*** | (0.002) |
| Dummy type of payment | -0.4372*** | (0.003) |
| Log Market Cap Acquirer | 0.0163*** | (0.001) |
| Log Market Cap Target | 0.0253*** | (0.002) |
| Log Revenue Acquirer | -0.0046** | (0.001) |
| Log Revenue Target | 0.2009*** | (0.001) |
| Dummy Multiple Acquirers | 0.0383*** | (0.004) |
| LOG Time in the Market Acquirer | -0.0551*** | (0.001) |
| LOG Time in the Market Target | -0.0247*** | (0.001) |
| Prior M&A Experience Acquirer | 0.3911*** | (0.006) |
| Prior M&A Experience Target | -0.0804*** | (0.002) |
| D_T | -0.1221*** | (0.003) |
| D_Fin | -0.3851*** | (0.003) |
| Dummy National or Cross Border Deals | 0.5104*** | (0.003) |
| Interaction_GDP_Cross | 2.3160*** | (0.074) |
| Interaction_AI_D_Fin | 0.1179*** | (0.006) |
| Interaction_AI_D_T | 0.0226* | (0.009) |
| Interaction_AI_Log_Market_Cap_Acquirer | -0.005** | (0.002) |
| Const | 1.3299*** | (0.007) |
| No. Observations | 140,000 | |
| R - sq | 0.196 | |
| Adj. R – sq | 0.196 | |
| p-values in parentheses<br>* p<0.05, ** p<0.01, *** p<0.001 | | |

Statistical analysis performed using Python with Monte Carlo simulation

The coefficient of the Log Value implies that larger deals with higher log values take longer to complete. This as we saw in Chapter Two could be due to the greater complexity and regulatory hurdles involved in larger transactions. GDP Acquirer has a strong positive effect on Time to Completion, suggesting that acquisitions by firms in stronger economic contexts tend to take longer and the GDP Target shows the exact opposite result, suggesting that deals where the target is from a stronger economy may be completed more quickly. This could reflect the target firm's smoother regulatory environments in countries with good economic conditions. The Ownership Structure Acquirer variable shows a negative coefficient, indicating that non-listed companies (since the binary variable was 0=public companies, 1=private) tend to complete deals faster. This could be due to the greater efficiency of private companies and less regulatory frameworks than public companies, for example like Private Equity Firms in the financial services sector. Similarly, Ownership Structure Target has a negative effect confirming the reduced timing in negotiations involving non-listed companies. The Dummy Type of Payment variable is negative, meaning that when cash forms of payment are used, deals tend to be completed faster. Both Log Market Cap Acquirer and Log Market Cap Target are positively associated with Time to Completion, suggesting that larger firms tend to have lengthier deal processes, likely due to their complexity, regulatory scrutiny, and the need for deeper due diligence. The coefficient for Log Revenue Acquirer is slightly negative, indicating that an increase in the acquirer's revenue (measured in log form) is associated with a marginal decrease in the Time to Completion, suggesting that larger acquiring companies, in terms of revenue, tend to complete deals slightly faster. One explanation is that larger companies have more experience and resources for handling M&A activities, which allows them to conduct the due diligence and negotiation processes more efficiently but, given that the coefficient is very small, the actual effect of the acquirer's revenue on the deal duration is minor. Instead, the coefficient for Log Revenue Target is positive and quite substantial, indicating that an increase in the target company's revenue is associated with a longer Time to Completion, because larger target companies are likely more complex, with a more operations, assets, legal and financial factors to consider during due diligence. The bigger the target company, the more time may be required for the acquiring company to evaluate all the relevant aspects as demonstrated by Log Value. This result in fact, leads us back to the interpretation of the log value since market cap and revenue are a measure of the companies' size involved, just like the higher value of deal which is likely paid from the larger companies. Even the Dummy Multiple Acquirers shows a positive coefficient as expected, given that as the number of buyers involved in an M&A transaction increases, the complexity of the agreements necessarily increases, due to multiple stakeholders involved from the complicated negotiation phase. The positive coefficient for Prior M&A Experience of the acquirer suggests that buyers with past experiences of M&A transactions slow down the process, which may be because an experienced acquirer is more careful in the negotiations, seeking advantageous conditions requiring more time in the complex due diligence phase. In contrast, a negative coefficient in the case of Prior M&A Experience of the target might indicate that a target with some prior M&A experience would be much better prepared than a target doing it for the first time, considering that these firms have been in the market on average for less time than the acquirer (see Table 1), who can often leverage this experience advantage on his side. So, having recent M&A experience can help the target defend against aggressive buyer strategies and be found prepared. The positive coefficient for the Dummy National or Cross-Border Deals indicates that international deals tend to take longer to complete. This is consistent with existing literature, which highlights that cross-border deals are often more complex due to cultural, regulatory and legal differences, which slow down the process since companies must manage many variables like local governance rules and geopolitical risks. The negative coefficient for D_T suggests that firms in the technology sector complete their M&A transactions more quickly. This expected result reflects the fact that tech firms are implementing AI systems. Similarly, the negative coefficient for D_Fin suggests that M&A deals in the financial sector tend to be completed more quickly. This may be due to financial firms are more familiar with the M&A process, since they operate in an industry that requires efficiency and compliance. Finally, the interaction terms: the first three are all positive, indicating that the interaction between AI and technology-related firms and finance-related, and between GDP and national/cross-border deals plays increase the Time to Completion. These interactions suggest that the effects of AI and GDP vary based on the context of the deal. The D_T variable, is positively associated with Time to Completion and this seems counterintuitive but, considering complexities like intellectual property rights, patents, intricate valuation software or AI could have uncovered hidden complexities and risks such as cybersecurity risks or compliance gaps that could implement the duration of the deal, or the implementation of AI could have suggested a strategic shift in the negotiation, prolonging the duration to align the strategies with AI-driven findings. Similarly, the positive coefficient on the interaction between AI and D_Fin could be for several reasons: the heavy regulation of this sector and the application of AI in highly sensitive financial deals may introduce additional layers, AI tools could flag more potential risks that need further investigation, an initial learning curve in which companies are not yet fully equipped to integrate AI into their deal-making processes, leading to inefficiencies or delays as companies adapt to the use of AI. Then the interaction between GDP and national or cross border deals is significantly positive as expected, since it involves deals in advanced economies between companies from different nations, increasing the complexity of the transaction. The last interaction between AI and the Log Market Cap of the acquirer shows a negative coefficient, which means that deals with very large companies as buyers that have implemented new technologies can streamline the process and reduce the Time to Completion of the deal. The statistic tests of the regressions indicates that there is no autocorrelation in the residuals (Durbin-Watson statistic) and that the residuals are not normally distributed (Jarque-Bera test).

The second OLS regression, shown in Table 8, introduce precise assumptions about the industries of the newly generated "twin" companies. The 80% of the simulated D_T or D_Fin companies introduced the use of AI in the deal, while 20% of the companies in these two industries did not. In contrast, in the rest of the sectors, 20% of the new companies integrated AI systems, while the rest 80% did not. Even if we applied two distinct modifications to perform the Monte Carlo Simulations, the results are very similar since the interpretation of the coefficient in this model gives us the nearly the same results, but with different magnitude. After considering how the modification of one particular detail may affect the firm characteristics (such as the company size or the age), this regression confirms the results we obtained, demonstrating how AI effectively impacts and reduces Time to Completion.

Table 8: OLS Regression by Monte Carlo Simulation with Industry Assumptions

| **OLS regression results with Monte Carlo Simulation** | **Dependent Variable: Time to Completion** | |
|---|---|---|
| **Variables** | **Coefficient** | **Standard errors** |
| Log Value | 0.1974*** | (0.006) |
| Dummy type of payment | -0.4712*** | (0.009) |
| Use of AI | -0.0439*** | (0.007) |
| Log Market Cap Acquirer | 0.0076** | (0.003) |
| Log Market Cap Target | 0.0284*** | (0.005) |
| Log Revenue Target | 0.2120*** | (0.004) |
| Dummy Multiple Acquirers | 0.0482*** | (0.012) |
| LOG Time in the Market Acquirer | -0.0608*** | (0.003) |
| LOG Time in the Market Target | -0.0256*** | (0.003) |
| Prior M&A Experience Acquirer | 0.4003*** | (0.021) |
| Prior M&A Experience Target | -0.0778*** | (0.007) |
| D_Fin | -0.3246*** | (0.009) |
| Dummy National or Cross Border Deals | 0.5572*** | (0.009) |
| Ownership structure Acquirer | -0.2982*** | (0.009) |
| Ownership structure Target | -0.0859*** | (0.007) |
| GDP Acquirer | 4.4560*** | (0.277) |
| GDP Target | -2.2610*** | (0.233) |
| Interaction_GDP_Cross | 2.2559*** | (0.250) |
| Const | 1.3018*** | (0.024) |
| No. Observations | 140,000 | |
| R - sq | 0.187 | |
| Adj. R – sq | 0.187 | |
| p-values in parentheses<br>* p<0.05, ** p<0.01, *** p<0.001 | | |

Statistical analysis performed using Python with Monte Carlo simulation

**Conclusion**

In this chapter, we performed two distinct simulations, each modifying one aspect of the dataset, yet both aimed at understanding the impact of AI on Time to Completion. The first simulation focused on reducing Time to Completion by 20% based on a normally distributed independent variable (AI), while the second modified other parameters such as the probability of introducing AI by technological and financial firms. Despite these variations in methodology, the results from both simulations were consistent in several aspects, which strengthens the robustness of the findings. Use of AI emerged as a significant factor in reducing Time to Completion across both simulations, since both models showed a negative relationship between AI and time efficiency, indicating that firms leveraging AI technologies can streamline this process consistently. This reinforces the hypothesis of the study, supporting the idea that AI has a measurable and beneficial impact on M&A processes. Other control variables such as Log Market Cap, GDP, and Ownership Structure displayed similar behavior in both simulations, showing the stability of these variables in influencing the time completion of the deal. Larger acquiring firms consistently extended the completion time due to careful investigation in the due diligence phase, while younger but with previous M&A experience firms were able to reduce it. Both simulations produced similar results despite different model inputs, suggesting that the results are robust and not overly sensitive to specific assumptions or noise introduced in the simulation.

One notable limitation of these findings is the restricted size of the real-world sample, which the Monte Carlo method tried to compensate by simulating multiple scenarios. While this methodology provides statistical robustness, further validation on larger dataset with real data would provide stronger empirical backing. Additionally, certain factors, like industry characteristics, were not captured in these models and could need further exploration in future research. The next chapter will focus on the ethical implications of the implementation of AI in general and in the M&A process.

## CHAPTER IV
## ETHICAL CONSIDERATIONS OF AI IN GENERAL AND IN M&A

### Introduction

AI brings not only opportunities but also significant ethical challenges. This chapter explores the ethical considerations in the implementation of AI technologies, both in a general business context and specifically in M&A transactions. AI's ability to process vast amounts of data and influence important decision-making raises concerns related to bias, privacy, transparency and demonstrate the need of a strong regulation about AI technologies.

In the first part of the chapter, the broader ethical issues concerning AI are examined, including the risks of biased algorithms, potential violations of privacy, and the challenges of ensuring accountability when AI systems make decisions. Moreover, the chapter discusses the urge for international regulations to govern the use of AI, aiming to balance innovation with ethical responsibility.

The second section shifts focus to the specific implications of AI in M&A deals. The increased efficiency in M&A transaction and the less cost associated to the use of AI represent a danger to everyone involved in these deals. As AI-driven tools become more prevalent in due diligence, valuation, and integration processes, concerns about data privacy, transparency, and the fairness of AI-driven decisions become more acute. There is the need to counterbalancing time and cost efficiency with ethical aspects to avoid the urges of the market weighing on the shoulders of ordinary workers. Therefore, the impact of AI on the workforce, particularly in terms of job displacement, highlights the need for ethical considerations around its implementation. The chapter concludes with a discussion on the importance of regulating AI's role in M&A to ensure fairness and responsibility throughout the deal process.

### 4.1 Ethical Considerations of AI

In analyzing the impact AI has had in many areas, the focus has been on the positive consequences, but it is also important to consider the disadvantages that the introduction of this technology brings.

There are not solely benefits as automating repetitive tasks, solving complex problems, reducing human error, improving customer experience and advancing medicine and healthcare. AI also comes with profound ethical challenges and risks that need to be addressed across different areas. The first two major consequences that come to mind concern the effect of technology on jobs and the environment. The ability of AI and ML models to automate processes and work quickly and without breaks for long periods of time could result in human workers losing their jobs, and this is inevitable, as history teaches, whenever a scientific innovation is introduced. However, the relocation of jobs can be regulated and does not necessarily have a negative meaning; in fact, it can lead to the creation of new jobs, for example, for the control and maintenance of new technologies. Another major problem concerns the significant amount of energy that AI systems require on a large scale to process data. This can lead to high environmental costs, resulting in increased carbon emissions and water consumption. Therefore, ethical considerations are critical in AI implementation for ensuring that AI systems are developed and used in a fair manner (The IEEE Global Initiative 2.0 on Ethics of Autonomous and Intelligent Systems, 2024; European Commission, 2024).

### 4.1.1 Bias and Fairness

Since AI models are trained and coded by humans, this exposes the risk that AI may be trained on data that reflect biased human decisions, leading to biased or discriminatory results against certain demographic groups. Here the main ethical concern about AI is the risk of algorithmic bias. Because they are based on large amounts of historical data, machine learning-based systems make decisions by relying on those assumptions. If the data used in training models contain inherent biases (gender, racial, or for socioeconomic reasons), AI can inadvertently replicate or even worsen existing biases present in the data used to train them. Even big organizations with the noblest of intentions can be affected by this, because the logic behind an efficacy computer depends on the data's quality it processes. Therefore, it is critical for AI professionals to identify the biases implicit in strategies, even though it can be very difficult. This problem becomes relevant when considering biased functioning AI that may reinforce inequalities in areas such as loan approvals (lending), legal sentencing (in criminal justice), and hiring. They should not unfairly advantage or disadvantage individuals or groups based on protected characteristics such as race, gender, or age, ensuring fairness and non-discrimination (J. Levy, Y. Lu, M. Montivero, O. Ramwala, 2023).

This phenomenon is called “Hallucinations.” Artificial intelligence systems can be inaccurate by create hallucinations when trained on biased or insufficient data, thus generating false information. To address the algorithmic bias, it may be useful to develop bias detection and mitigation strategies, paying particular attention to the data used to train AI models. Solving these problems requires careful attention to the design and implementation of AI systems, as well as ongoing monitoring and evaluation to detect and address any biases that may emerge.

A recent example of this phenomenon occurred in the Netherlands, where an AI system trained on biased data was used by tax authorities to label thousands of people as fraudsters. The system was named SyRI (Systeem Risico Indicatie), and it was supposed to allocate social benefits. Instead, it profiled citizens based on their tax returns, leading to unjustified suspicions of fraud. The result was that 20,000 families had their benefits unjustly revoked. This scandal caused the Dutch government to resign and were raised concerns about privacy violations (related to the storage of lists of registered frauds) and human rights, particularly for the most vulnerable groups in society (Even the United Nations pronounce a formal stance concerning significant potential threats to human rights).

The discriminatory algorithm, used for three years by the municipality of Rotterdam, targeted mainly young single mothers, often with limited knowledge of Dutch, for fraud investigations without providing any explanations. The algorithm was based on biased and inaccurate data, producing unfair outcomes wrongfully reducing people's benefits. Despite objections from the Dutch Data Protection Authority and others this was done without transparency, and the system did not uncover new fraud cases but rather led to significant privacy violations (European Parliament, 2023).

Cases of algorithmic bias have also occurred in health care, as automation is becoming increasingly popular in this area as well. It may be the case that, due to systematic oversights in the algorithm development phase in some health care applications, we end up disadvantaging patient populations that are already at greater risk of suboptimal health care delivery. Human biases encoded in collected data, for example, are a common cause of algorithmic bias. Consider an algorithm designed to rank whether a given patient should be referred to a certain health care program for complex medical needs or not. This algorithm worked by assigning lower risk scores to black patients than to white patients because the AI system was based on total annual health care costs as a quantitative measure of patients' care needs. However, due to racial biases, there is a tendency among black and white patients to spend fewer fiscal resources on the care of black patients even though their health care needs are the same. The problem therefore must be traced to the source: if the creators of the model did not take this bias into account, it is possible that the system is being used, automating the application of this bias. We must therefore prevent these biases with the goal of training models that are more sensitive to patient characteristics to promote equity and diversity (J. Levy, Y. Lu, M. Montivero, O. Ramwala, 2023)

To avoid injustices like this, there might be efforts to mitigate bias in AI systems by using representative training data and making models transparent. AI should be developed by organizations with ethical guidelines that focus on equity, inclusion, fairness and non-discrimination (O'Neil C., 2016).

### 4.1.2 Privacy

To perform effectively, AI systems require access to a wide range of sensitive information. Data stored by AI systems can often be collected without the consent of the user and may even be accessed by unauthorized individuals in the event of a data breach. AI systems raise significant privacy concerns because they rely on processing large amounts of personal data to make decisions. The balance between innovation and individual privacy has become very delicate since the proliferation of personalized advertising, facial recognition and AI-powered surveillance. The practice of tracking individuals without their consent with the use of AI or processing sensitive data without adequate safeguards becalmed a risk to civil liberties. To protect the rights of individuals and prevent misuse of personal data, it is necessary to ensure their privacy. Some new privacy-enhancing techniques, such as data anonymization and encryption, have been introduced to help protect privacy in AI systems. Recently, several privacy frameworks have emerged to address these concerns, but there is a complex legal framework surrounding data protection, which vary across different jurisdictions. Companies must ensure that their AI systems comply with all applicable laws such as the General Data Protection Regulation (GDPR) in Europe introduced in 2018 to limit the misuse of AI-based technologies to protect personal data and respect the consumer privacy. The implementation of the GDPR has also raised concerns about how data protection may affect deals. A study conducted by Euromoney Thought Leadership Consulting in 2019, involving more than 500 M&A professionals across Europe, the Middle East, and Africa (EMEA), revealed that the GDPR has had a significant impact on the M&A process for many companies. The reported data shows that among the M&A professionals surveyed, 55% confirmed having experienced unsuccessful negotiations specifically due to GDPR compliance, which raised concerns about the data protection practices of the target company. However, as AI continues to evolve, privacy regulations need to adapt to keep up with the pace of technological change. (AI and Ethics: Privacy and Big Data, 2024; Future of Privacy Forum, 2020; General Data Protection Regulation, 2016)

In May 2024 the EU introduced the first legally binding international treaty in this field to protect human rights from AI. The Council of Europe Convention has been signed by the USA and other non-EU countries and requires regulation of the entire AI system lifecycle, with a focus on privacy protection, accountability and transparency. This legal obligation is based on key principles such as human dignity and equality. The framework Convention mandates preventive management of potential negative impacts through its risk-based approach, urging states to ban technologies that are incompatible with fundamental rights. (Council of Europe Framework Convention on AI, 2024).

### 4.1.3 Accountability

Another critical issue regarding the ethical use of AI involves the lack of transparency of AI tools that can lead to distrust and uncertainty among users, as their decision-making processes are not easily explainable. From health diagnostics to autonomous driving to financial trading, when AI systems make decisions, who is responsible if things go wrong? Transparency and explainability in AI systems are essential to building trust and accountability, enabling users to understand how decisions are made and challenge them when necessary. What complicates accountability is the concept of AI as a “black box,” where the decision-making process is opaque and not easily interpreted. If an AI system makes a decision that creates harm, determining who is responsible (between the organization deploying the AI, the user, or the developer) can be difficult. In AI systems ensuring accountability is crucial and to establish clear lines of responsibility for AI decisions is necessary build a mechanism to hold individuals and organizations accountable for any harm caused by AI systems. The ethical concern here is that AI systems could be developed in a non-transparent manner, resulting in a lack of explanation for harmful AI decisions and a negative impact on users and businesses. AI guidelines should include transparency, traceability, and human oversight. There must be AI systems where humans can intervene in critical decisions and AI processes can be transparently audited to ensure accountability. Although AI systems can automate many tasks, human oversight must be maintained to ensure that AI decisions align with ethical and legal standards. Humans play a key role in ensuring responsible AI use, as well as detecting and correcting errors. As AI systems become increasingly powerful, influencing areas such as employment, healthcare, and education, it is crucial to consider their cultural and social impacts. Designing and implementing AI systems with these considerations in mind is essential to ensuring that they promote positive outcomes for society (Russell S., 2019).

### 4.1.4 Autonomy and Control

As these systems become more intelligent, questions arise about the degree of autonomy AI systems can handle, and how much control humans should retain over AI decisions. Concerns about increasing AI autonomy arise in fields such as self-driving cars, autonomous weapons, or high-frequency trading, regarding the transfer of too much decision-making power to machines. The ethical implications of AI autonomy can be addressed by maintaining human oversight to ensure that AI operates within the bounds of social norms and human values.

### 4.1.5 AI Regulation

As AI grows in complexity and power, lawmakers around the world are looking to regulate its use and development. The first major step was taken on August 1, 2024, when the European Union passed the Artificial Intelligence Act, which aims to ensure that AI systems are "safe, transparent, traceable, non-discriminatory and environmentally friendly." Other countries such as Brazil and China have introduced measures to regulate AI (AI Act enters into force, 2024).

In the United States, however, AI regulation is still ongoing as the Biden-Harris administration introduced a non-enforceable AI Bill of Rights in 2022, and the Executive Order on Safe, Secure, and Trustworthy Artificial Intelligence was introduced in 2023, which aimed to regulate the AI industry without limiting the growth of the sector, maintaining the country's status as a technology leader. Congress has repeatedly attempted to pass stronger legislation but has failed, leaving no law in place to regulate the risks of AI or limit its use. In fact, now, all legislation on AI in the United States only exists at the state level. (Glover E., 2024)

AI systems in financial services must also be developed and used in a way that respects ethical principles. There is a need for regulatory frameworks for developers and users to understand the ethical issues that may arise in AI systems. Prior to the latest legislations just mentioned, several initiatives have been proposed to regulate ethical AI, such as the IEEE Global Initiative for Ethical Considerations in AI (2016) and Autonomous Systems and the OECD Principles on AI (2019), which assesses the opportunities and policy challenges of AI by analyzing how it changes the way people learn, work, and interact with this technology. These frameworks were intended to provide guidance on the ethical practices of AI to help financial institutions in developing their own ethical guidelines (Uzougbo N., Ikegwu C., and Adewusi A., 2024).

### 4.2 Ethical Considerations of AI in M&A deals

New technologies have also affected the M&A world, increasingly reshaping the way deals are identified, negotiated, and executed. It has quickly become a valuable tool in this field because AI can analyze large data sets and identify risks or synergies that may not be obvious to human analysts. However, this application of AI also raises several ethical concerns specific to the context of mergers and acquisitions.

#### 4.2.1 Bias in M&A

As previously discussed, AI systems are only as impartial as the data on which they are trained. In M&A activities, this issue could represent a significant challenge, as the detection of distorted historical data during the due diligence phase leads to distorted analyses and decisions. For instance, during the search and evaluation of a potential acquisition target, if the implemented AI system is trained on data containing incomplete information or grounded in historical biases, it might decide to favor or exclude certain market opportunities, resulting in substantial consequences. Indeed, this decision could lead to potential gaps in strategic alignment or severe losses due to a bad advised investment (The Impact of AI on Mergers and Acquisitions, 2024).

#### 4.2.2 Data Privacy and Security in Due Diligence

One of the key areas in the first stages of the M&A process is due diligence. In this phase, AI is used to analyze vast amounts of sensitive data from both the target and the acquirer and since that AI tools can quickly sift through operational data, legal documents and financial records to identify risks and opportunities, it becomes a valuable resource to accelerate this process. However, the use of AI in this phase poses potential security risks and data privacy (Deloitte Insights, 2019).

If AI systems lack robust security measures, some sensitive corporate information could be exposed or mishandled. Moreover, using AI-based tools in cross-border transactions can generate issues regarding data sharing across jurisdictions, as universal privacy laws do not yet exist. Only recently has there been an effort to ensure compliance with regulations such as the GDPR, but unfortunately these are not yet laws that apply to all states. In conclusion, the significant ethical challenge in AI-driven M&A lies in simultaneously balancing the need for thorough due diligence with privacy safeguards (M&A Due Diligence in the Digital Age, 2024).

### 4.2.3 Transparency and Fairness in Decision-Making

Another risk that AI models can pose is when assessing the value of companies and predicting post-deal synergies or risks after the transaction. Here there is a risk that AI will make recommendations based on partial or incomplete data, undermining the transparency of the negotiation process and leading to decisions that could unfairly favor one party over the other.

Another related issue concerns the integrity of M&A transactions, which is critical to ensure that AI-driven valuations are fair and transparent. Indeed, AI tools used to automate deal structures can undervalue some intangible assets, such as human capital or brand value, which are more difficult for AI to quantify, leading to a biased valuation. (McKinsey & Company, 2020, Coeckelbergh M., 2020)

### 4.2.4 Job Displacement and Workforce Impact

Another ethical consideration relates to one of the major fears of the new technological era: AI-powered mergers and acquisitions can lead to potential job displacement. Jobs previously done by employees could be automated through AI-driven efficiency and automation, and this would mean major post-deal restructuring. Although this would lead to increased profitability and efficiency, on the other hand it raises several social responsibility concerns on the part of the acquiring company, which must expose to make difficult decisions. From an ethical point of view, companies involved in mergers and acquisitions cannot just consider the economic side of the deal to succeed in limiting expenses but must keep in mind the impact of AI-driven decisions on the workforce, to try to balance profitability with employee welfare. The answer to this problem could be to offer retraining programs to employees of the target company or consider including human factors in post-merger integration strategies (Coeckelbergh M., 2020)

#### 4.2.5 Ethical Use of Predictive Analytics

One of the most powerful resources regarding AI is predictive analytics, which can provide insights into market trends, future performance, and risks, for example, in evaluating a potential new deal. However, the ethical use of these predictions is critical as there is a risk of relying too much on these predictive models, coming to overly risk-averse or exploitative decisions without proper evaluation. An example of this bias could occur when AI models predict negative performance for a particular market segment, causing layoffs or restructuring that could have been avoided with a more nuanced understanding of the business environment. This is why ensuring ethical use of AI in M&A is critical and means striking a balance between data-driven decision making and human judgment, without neglecting the social and economic impact of AI-based predictions. AI is a powerful tool capable of processing data and predictive insights, but human judgment and experience are critical to making strategic decisions. Although AI offers immense potential to transform the M&A landscape, the real strength lies in creating synergy between AI capabilities and human judgment. This is to ensure that AI remains a tool in the service of efficiency to enhance its results (The Social and Ethical Impact of M&A, 2019).

#### 4.2.6 How AI Buyers Can Mitigate Risks

Acquiring AI companies presents a range of significant risks that inhibit value creation in the context of M&As, that carries ethical implications that must be addressed during the pre-deal due diligence phase. The first risk they incur is a commercial risk as sellers show the commercial value offered by their AI systems without considering that these systems can be surpassed by commercially available AI technologies in a few years. In that case, the potential revenues generated by the deal would be limited. Another risk is technological; in fact, post-acquisition AI integration requires the development of comprehensive data management and software development platforms. This can only be there if the acquirer has solid technological capabilities, which it may not have. To proceed with the due diligence phase, a large amount of data about the target company is needed, much of which may be sensitive consumer or proprietary information. If this data is not properly protected from cyber-attacks, can lead to significant ethical and legal concerns, especially in regions with stringent data protection regulations, such as GDPR-compliant territories. Any failure to secure this data could result in serious legal liabilities for the buyer, raising ethical questions around the handling and protection of sensitive information post-acquisition. These steps show a perfect example of how essential is for buyers to responsibly and successfully leverage AI acquisitions for sustainable value generation. The engine of an AI platform is primarily driven by the data that fuels its algorithmic operations. However, the data owned by the seller is considered sensitive and governed by regulatory restrictions. Therefore, the seller must protect this data from unauthorized access through robust cybersecurity measures and protocols to minimize data security risks. An accurate assessment of these risks and the implementation of mitigation strategies would facilitate buyers to create value in the post-acquisition stage. (KPMG The Ethical Implications of AI in M&A, 2023).

### 4.2.7 Regulating AI in M&A

When integrating AI into M&A, numerous regulatory obstacles emerge due to the complex navigation of global regulations that lack universal applicability. Specifically, the deployment of AI in these processes can trigger an antitrust investigation, as various regulatory frameworks require that the use of algorithms in decision-making processes be transparent and justifiable. The already intricate regulatory landscape is further challenged in sectors such as finance or healthcare, where regulations concerning the application of AI are more stringent. This situation necessitates significant and continuous efforts by companies to remain informed about current and emerging regulations, to ensure that there are no unintentional violations during the use of AI systems (The Impact of AI on Mergers and Acquisitions, 2024).

### Conclusion

While AI offers numerous advantages in the M&A process, it also introduces specific challenges and limitations that needs human supervision and that organizations must navigate carefully to fully leverage its potential. AI presents significant opportunities to improve efficiency, accuracy, and insight in M&A, but it also introduces several ethical considerations that must be handled carefully. To preserve the integrity of the M&A process, it is essential to ensure that AI-driven instruments have certain nonnegotiable characteristics: they must be fair, transparent, and accountable. In addition, the next step, as AI continues to evolve, is for regulators to work together with the companies producing these technologies to remain vigilant about the ethical challenges posed by AI, balancing innovation with the protection of human and social values that must remain a priority in this area as well. With the advancement of technological development, it is likely that AI will become an increasingly integral part of the M&A process, offering improvements in the identification, evaluation, and integration of acquisition targets, thereby representing a significant competitive advantage for companies. This evolution, beyond the technical perspective, will assist organizations in undertaking M&As that are more advantageous from financial, environmental, and social standpoints, by integrating ESG (Environmental, Social, and Governance) and EHS (Environmental, Health, and Safety) considerations into M&A strategies. (The Impact of AI on Mergers and Acquisitions, 2024).

On the other hand, the increasing sophistication of AI will still contribute to concerns about the rise of increasing misinformation, the threat to privacy, and the risk of job losses. In a future now more likely than ever, questions also persist about the possibility of AI surpassing human understanding and intelligence, a phenomenon known as the technological singularity that in the imagination of technology not subject to human oversight could lead to multiple moral dilemmas as well as unpredictable risks.
Looking ahead, it is crucial to advance the understanding of the ethical and legal implications of AI in financial services. Ongoing research is needed to develop fairer algorithms, AI techniques that protect privacy, and regulatory frameworks that safeguard consumer rights without compromising innovation. By broadening the community of people working together in this field, the integration of AI into financial services can be achieved in a way that upholds transparency, accountability, and ethics. In conclusion, protecting consumers and promoting the responsible use of technology in finance are essential to ensuring legal accountability and ethical considerations in the use of AI. This also helps build trust within the community. Addressing these ethical challenges fosters innovation while unlocking AI's potential to create positive outcomes for society in a way that is transparent and explainable (Uzougbo N., Ikegwu C., and Adewusi A., 2024; The Social and Ethical Impact of M&A, 2019).

**CONCLUSION**

The aim of this thesis was to explore the innovative role of AI and ML in the M&A process. In the first chapter we discussed the fundamental concepts of the new technologies and how they are becoming an integral part to achieve success into the financial and business sector. Then we presented how AI can revolutionize several stages of the M&A deals, although, the literature review that provided the basis for the empirical analyses and the simulations in the next chapters, highlighted gaps in the current research, particularly regarding the quantifiable impact of AI on transaction efficiency. Then we presented the core results obtained through OLS regression analyses on real data on M&As, which, despite the small sample size of 140 observations, provided initial evidence of AI's positive influence on reducing Time to Completion and affecting some determinants of Cost Efficiency. Despite the small size of dataset, which prevented stronger conclusions, the findings offered valuable insights and set the stage for further exploration. With this assumption we addressed the limitations of the small sample size by applying Monte Carlo method to generate a larger dataset by duplicating our sample creating "twin" companies, to introduce some noise. The simulations confirmed the initial findings from the empirical analysis and allowed for a deeper examination of how AI affects M&A performance under more extreme conditions. We highlighted that AI accelerates the duration of deals enhancing decision-making in terms of deal structure and risk management, showing that AI has a substantial role to play in the future of M&A transactions. The final part expanded the scope of the discussion to consider the ethical challenges associated with AI within the M&A context to underline issues such as bias, transparency, and data privacy. Particularly in high risks environments like M&A, where decisions can have profound financial and social impacts, is fundamental to address these issues with robust regulations to ensure that AI is used ethically.

This thesis aims to recognize the potential of AI in revolutionizing the M&A process, contributing to the growing body of literature regarding this area. However, the research also highlights some limitations regarding the technology, such as ethical implications in its use. In addition, the very limited set of real-world observations is an obstacle to generalizing the data as universal evidence for M&A. In the future, should be conducted empirical analyses tested on much larger samples that can replicate the variety of the global landscape. The combination of empirical analysis and simulation-based modeling provides a valuable foundation for future research, as it confirms the opportunities for companies engaged in M&A to reduce costs and processes through AI, to gain a competitive advantage in terms of speed, accuracy and results. However, as the use of AI increases, so does the need to avoid the scarification of ethics and human rights in favor of operational efficiency.

Looking ahead, future research should focus on expanding the dataset used to conduct empirical analyses that may also include considerations regarding geographies and industries of AI application in M&As to explore different combinations of outcomes and assess the implications of using technology with a universally valid method, as AI and ML have the potential to reshape this industry.

**APPENDIX**

**1-Explanatory variables**

Table 4

| N° | Name | Meaning | Calculation method |
|---|---|---|---|
| 1 | Log Value | Logarithm of the transaction value | Log (Total value of the deal) |
| 2 | Dummy type of payment | 1 = Cash, 0 = Stock | Binary, based on payment method |
| 3 | Use of AI | 1 = AI used, 0 = AI not used | Binary variable |
| 4 | Log Market Cap Acquirer | Logarithm of acquirer's market capitalization | Log (c+1) |
| 5 | Log Market Cap Target | Logarithm of target's market capitalization | Log (z+1) |
| 6 | Log Revenue Acquirer | Logarithm of acquirer's revenue | Log (v+1) |
| 7 | Log Revenue Target | Logarithm of target's revenue | Log (t+1) |
| 8 | Dummy Multiple Acquirers | 1 = Multiple acquirers, 0 = Single acquirer | Binary variable |
| 9 | LOG Time in the Market Acquirer | Logarithm of acquirer's time in the market | Log (Company age) |
| 10 | LOG Time in the Market Target | Logarithm of target's time in the market | Log (Company age) |
| 11 | Prior M&A Experience Acquirer | 1 = Acquirer has M&A experience, 0 = No experience | Binary variable |
| 12 | Prior M&A Experience Target | 1 = Target has M&A experience, 0 = No experience | Binary variable |
| 13 | D_T | 1 = Technology sector, 0 = Non-tech | Binary variable |
| 14 | D_Fin | 1 = Financial sector, 0 = Non-financial | Binary variable |

| | | | |
|---|---|---|---|
| 15 | Time to Completion | Time to complete the transaction | Measured in days (or scaled as days/100) |
| 16 | GDP Acquirer | Acquirer country's GDP percentage | GDP growth rate (%) |
| 17 | GDP Target | Target country's GDP percentage | GDP growth rate (%) |
| 18 | Dummy National or Cross Border Deals | 1 = Cross-border, 0 = National | Binary variable |
| 19 | Ownership Structure Acquirer | 1 = Private, 0 = Public | Binary variable |
| 20 | Ownership Structure Target | 1 = Private, 0 = Public | Binary variable |
| 21 | Post Deal Integration Strategy | 1 = Integration successfull, 0 = No, failed | Binary variable |
| 22 | Interaction_GDP_Cross | Interaction between GDP and cross-border deals | Product of GDP and Cross-Border Deal variable |
| 23 | Interaction_AI_Type_of_Pay ment | Interaction between AI use and type of payment | Product of AI and Type of Payment variable |
| 24 | Interaction_AI_Prior_MA_Ta rget | Interaction between AI use and target M&A experience | Product of AI and Prior M&A Target variable |
| 25 | Interaction_AI_D_T | Interaction between AI use and technology sector | Product of AI and D_T variable |
| 26 | Interaction_AI_D_Fin | Interaction between AI use and financial sector | Product of AI and D_Fin variable |
| 27 | Interaction_AI_Log Market C ap Acquirer | Interaction between AI use and acquirer's market capitalization | Product of AI and Log Market Cap Acquirer variable |

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