The Art of AI -

The Impact of Artificial Intelligence on the Merger & Acquisition Strategy

Alexander Rien

Dissertation written under the supervision of
Gonçalo Saraiva

Dissertation submitted in partial fulfilment of requirements for the MSc in International Management, at the Universidade Católica Portuguesa, 20.12.2018.

ABSTRACT

Title: The Art of AI - The Impact of Artificial Intelligence on the Merger and Acquisition Strategy

Author: Alexander Rien

Based on a lack of studies in this specific field and the theory that manual as well as cognitive tasks can be replaced by machines, this study explores, using a qualitative research method, the impact of artificial intelligence on the Merger&Acquisition process. An analysis of multinational interviews with experts from different industries and a framework adapted to the Due Diligence process show that there is and will be an impact of Artificial Intelligence on the Due Diligence process as the most crucial process of the Merger& Acquisitions. Although the impact of Artificial Intelligence is nowadays the greatest on Legal Due Diligence and AI-based solutions are already offered, this study, however, states that within the next 5-10 years, even 96% of all tasks of the Due Diligence will be partially or fully substituted. Furthermore, the framework reinforces the underlying theory that both manual and cognitive tasks can already be replaced by machines. Among the reasons why AI has nowadays not yet been adopted in all Due Diligence are the fact that the target companies' data is too different to train a machine, that due diligence involves a lot of communication and that humans are not yet ready for this cultural change.

Based on these findings, managers of companies conducting due diligences are advised to prepare their company and employees for the implementation of Artificial Intelligence by following the steps described in Kotter's 8-step change model.

Keywords: Merger & Acquisition | M&A | Artificial Intelligence | AI | Due Diligence | Legal Due Diligence | Financial Due Diligence | Commercial Due Diligence | Machine Learning | Deep Learning | Natural Language Processing | Clustering

SUMÁRIO

Título: A arte da AI - O Impacto da Inteligência Artificial na Estratégia de Fusão e Aquisição

O autor: Alexander Rien

Baseado na falta de estudos neste campo específico e na teoria de que tanto as tarefas manuais como as cognitivas podem ser substituídas por máquinas, este estudo explora, utilizando um método de pesquisa qualitativa, o impacto da inteligência artificial no processo de fusão e aquisição de empresas. Uma análise de entrevistas multinacionais com especialistas de diferentes indústrias e um quadro adaptado ao processo de Due Diligence mostram que existe e existirá um impacto da Inteligência Artificial no processo de Due Diligence como processo mais crucial do Merger& Acquisitions. Embora o impacto da Inteligência Artificial seja atualmente o maior em Due Diligence Legal e as soluções baseadas em IA já estejam disponíveis, este estudo, no entanto, afirma que nos próximos 5-10 anos, até 96% de todas as tarefas do Due Diligence serão parcial ou totalmente substituídas. Além disso, o framework reforça a teoria subjacente de que as tarefas manuais e cognitivas já podem ser substituídas por máquinas. Entre as razões pelas quais a IA ainda não foi adotada em todas as Due Diligences está o fato de que os dados das empresas-alvo são muito diferentes para ensinar uma máquina, que a due diligence envolve muita comunicação e que os humanos ainda não estão prontos para essa mudança cultural.

Com base nessas descobertas, os gerentes de empresas que realizam as devidas diligências são orientados a preparar suas empresas e funcionários para a implementação da Inteligência Artificial, seguindo os passos descritos no modelo de mudança de 8 passos de Kotter.

Palavras-chave: Fusões e Aquisições | Fusões e Aquisições | M&A | Inteligência Artificial | AI | Due Diligence | Legal Due Diligence | Financial Due Diligence | Commercial Due Diligence | Machine Learning | Deep Learning | Natural Language Processing | Clustering

ACKNOWLEDGEMENTS

First, I want to thank my supervisor, Gonçalo Saraiva, who supported me constantly along my thesis semester with his managerial and academic experience. In addition, I would like to thank all the interviewees who took the time to share their knowledge and experience with me. At this point, I especially like to address Aurimas Račas and Ravi Arora, who have always taken the time to thoroughly answer my many questions and requests. Best wishes to Japan and India.

Furthermore, I especially thank my parents who have supported me throughout my entire academic career and without whom I would not be where I am now, at the end of a great chapter and at the beginning of an even greater one.

I also thank my sister and my friends who all came to visit me in Lisbon and to whom I could show such a great city.

Finally, I would also like to say thanks to my girlfriend, who supported me during my entire studies and especially during this master thesis.

TABLE OF CONTENTS

TABLE OF FIGURES

TABLE OF TABLES

TABLE OF APPENDICES

GLOSSARY

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
M&A	Merger & Acquisition
DD	Due Diligence
LDD	Legal Due Diligence
FDD	Financial Due Diligence
CDD	Commercial Due Diligence
NLP	Natural Language Processing

1. CHAPTER: INTRODUCTION

"What all of us have to do is to make sure we are using AI in a way that is for the benefit of humanity, not to the detriment of humanity". – Tim Cook

1.1 Background and problem statement

Over the past few years, the number of M&A transactions have been growing to such an extent that one could almost describe it as an M&A boom (Platt, 2018). While M&A is, on the one hand, a relatively basic method of executing a growth strategy, it also entails considerable risks. According to a study by KPMG, approximately 70% of M&A transactions are not successful or do not add value (Martin, 2016). The DD as the most crucial part of an M&A is supposed to help to reduce this risk and assist in finding synergies between two companies. However, due to the increasing demand for an ever more sophisticated DD and increasingly complex transactions, problems have arisen in a way the DD is being conducted today. One of the major problems is the pressure, to carry out these ever more complex DD, with the simultaneous growth of the amount of data and documents to be reviewed, within a certain time. AI is supposed to help improve the process and overcome those problems. Based on a lack of studies in this specific field of the impact of technology on specific processes and the theory that manual as well as cognitive tasks can be replaced by machines (McAfee & Brynjolfsson, 2011), this study explores the impact of AI on the DD and therefore on M&A.

What is more, several companies have entered the market in recent years whose AI-based solutions are intended to serve as tools for more efficient, cost-effective and accurate processing. As these tools have only recently emerged and are not yet widely used, there is a lack of empirical evidence to show the need for such AI tools.

In this respect, the following research questions have been defined:

RQ 1: What are the main problems in the traditional way of doing DD *and can these problems potentially be solved by AI?*

RQ 2: What added value do the AI tools bring compared to the traditional DD?

RQ 3: Are there companies that already offer AI-based solutions for the DD*? If yes, how do the solutions look like and which problems do they solve?*

RQ 4: For which types of DD *can AI offer the greatest benefit?*

RQ 5: Which AI technologies and capabilities are being used by these companies?

RQ 6: Are there AI-based already solutions offered for all three DD*? If not, which are the reasons?*

RQ 7: Based on the findings, will AI now/ within the next 10 years have an impact on the DD *process and how much?*

The main objective of this work is to assess the current situation as well as to identify to what extent AI currently impacts and will in the future impact the traditional DD, including the LDD, FDD, and CDD. To answer these questions first literary, theoretical and historical research will be carried out. It examines which scientific findings already exist on this topic and provides at the same time a theoretical foundation for the empirical part of the work. Then an empirical investigation will be carried out using qualitative methods to analyze both the current situation and future trends. A quantitative approach, however, has not been chosen, as the use of artificial intelligence is not yet widespread and the technologies are still very young hence too little data is available to draw confident conclusions.

In the qualitative method, interviews will be conducted with qualified experts who have practical relevance, knowledge, and expertise in this field. This includes providers of AI tools and data rooms as well as management consultants and lawyers.

In order to test the underlying theory as well as to strengthen the conclusions of the experts, the task model created by Autor *et al.* (2003) is adapted in such a way that also the impact of AI on the DD process can be roughly quantified, so a trend can be seen.

1.2 Relevance

Although there exist many studies on the influence of machines on the labor market, there is still a lack of studies that investigate the impact of AI-based machines on a single process like the M&A. In case the findings of this work show an impact of AI on M&A, then this is especially important for companies that conduct DD, including management consultancies and law firms. The findings of this work will then provide such companies with a starting point for the implementation of AI and the incentive to undertake a corporate change in order to ultimately achieve an important competitive advantage.

1.3 Dissertation outline

The dissertation comprises a total of five chapters with the following structure. The first chapter is intended to give an introduction to the topic and the field of research and to present the existing problem as well as providing an overview of the work. The second chapter provides a theoretical foundation for the dissertation, in which the existing literature on both AI and M&A is displayed, discussed and analyzed. Thereafter, Chapter 3 introduces the explanatory part of the research by describing the methodology including the data collection process and sample characterization. Chapter 4 deals with the qualitative research part of the analysis. It includes the evaluation of the experts' interview results and the verification of the proposed theory. In the last chapter, conclusions are drawn and discussed in the context of the literature given. Finally, suggestions for future research are being made, implications for a manager on how to adapt the corporate culture to the change as well as limitations.

2. CHAPTER: LITERATURE REVIEW

The following chapter provides a theoretical framework on the Task Model, AI and M&As related to the main question of research and the purpose of this thesis. The topics have been examined with the help of previous research findings and a summary of academic results from various scientific journals as well as with the help of empirical research such as books and relevant articles.

The first part of this literature review describes the underlying theory of this dissertation as well as the model on which the analysis is partially constructed.

In the second part of the literature research, the M&A Strategy Process is then discussed and explained, as well as discussed whether the process is successful in the long term. Finally, the traditional DD process as key to a successful M&A transaction is explained.

The literature review concludes with an explanation of AI along with a description of its origin and history. Furthermore, the underlying technologies will be explained and shown which capabilities of this technology are already possible today.

The purpose of this literature research is to give the reader an overview of the management concept and the technology concept as a basis for the analysis.

2.1 Task Model

Although several frameworks and models exist that investigate the impact of computers on occupational employment composition (Frey & Osborne, 2013) (Bresnahan, Brynjolfsson, & Hitt, 2002), this dissertation bases on one model presented in a research by Autor *et al.* (2003). This research explores the skill content of recent technological changes and assesses a theory of how quickly computer technology will change the way people perform tasks in their workplace (Autor, Levy, & Murnane, 2003).

To test this theory, the authors developed a framework with the argumentation that work processes can be segmented into four groups. This framework will later, however, be used in the empirical part of this dissertation in an advanced form for the DD. After exploring data from 1960 to 1998, the authors found that computer-based technologies can be associated with reduced labor input of routine manual and routine cognitive tasks and increased labor input of non-routine cognitive tasks (Autor, Levy, & Murnane, 2003).

While tasks which can be executed by machines according to explicitly programmed rules are considered routine tasks, non-routine tasks are tasks where rules are not sufficiently understood to be written in code (Polanyi, 1966). Cognitive non-routine tasks were additionally further divided into analytical and interactive non-routine tasks, which is, however, not clearly illustrated in the following model. The definitions for the cognitive tasks were taken from the Handbook for Analyzing Jobs and are appended to this work in Appendix 1.

PREDICTIONS OF TASK MODEL FOR THE IMPACT OF COMPUTERIZATION ON FOUR CATEGORIES OF WORKPLACE TASKS

	Routine tasks	Nonroutine tasks
	Analytic and interactive tasks	
Examples	• Record-keeping • Calculation • Repetitive customer service (e.g., bank teller)	• Forming/testing hypotheses • Medical diagnosis • Legal writing • Persuading/selling • Managing others
Computer impact	• Substantial substitution	• Strong complementarities
	Manual tasks	
Examples	• Picking or sorting • Repetitive assembly	• Janitorial services • Truck driving
Computer impact	• Substantial substitution	• Limited opportunities for substitution or complementarity

Table 1 - Task Model (Autor, Levy, & Murnane, 2003)

Although the results of the academic work are significant and comprehensible, the results are to be viewed critically from today's point of view as the tests carried out are nevertheless based on outdated data as well as outdated technology. Furthermore, and this is illustrated in the last paragraph of this literature review, that some non-repetitive tasks listed in the Task Model such as Truck Driving or Medical Diagnosis are already feasible with modern technology today (McAfee & Brynjolfsson, 2011).

Also Frey and Osborne, with their research about the probability of computerization of a variety of professions, also prove that the theory that only non-routine tasks are replaced can be refuted. Even more, they show which specific professions are at risk of being substituted by a computer and which are not (Frey & Osborne, 2013).

What is more, by showing that even non-routine tasks can be replaced by machines, Polanyi's definition (1966) can no longer be valid, so that a new one is necessary. This, however, is not as simple, because in the literature there is no suitable definition of routine and non-routine tasks, so that this thesis will define routine tasks as tasks that can be learned beforehand and are repetitive and non-routine tasks as those that are performed infrequently, performed for the first time and cannot be trained upfront.

Finally, this thesis will be grounded on and further test the theory of Brynjolfsson *et al.* (2011) that both routine and non-routine and manual and cognitive tasks can be substituted by computers. Furthermore, since the task model created by Autor *et al.* (2003) still withstands the new theories it will be used to test this theory when it is applied to one single process.

2.2 M&A Strategy

The second part of the literature illustrates where the M&A process is to be classified within a strategy and explains why DD is the most crucial component. Since the M&A is also often referred to as a strategy on its own (Ogada, Achoki, & Njuguna, 2016) (Roche, 2002), this section begins with a discussion of how strategy can be defined.

2.2.1 Definition

The term "strategy" originally comes from the field of military policy and its history. In this respect, the use of the term "strategy" in the field of corporate affairs naturally suggests a warlike understanding of corporate competition, in which it is above all a matter of beating others (Keller, 2008). Approximately 2500 years ago the Chinese military strategist Sun Tzu wrote one of today's most popular strategy books "The Art of War", on which the title of this dissertation derives. Although Sun Tzu in his book doesn't define strategy, he explains what army is needed to win and survive wars (Tzu, 500 BC). Although the term strategy has been used in business administration for decades, there is unfortunately still no common definition (Steen, 2016), but rather a confusion what the term stands for.

Michael Porter, for example, defines in his paper "What is Strategy?" a strategy as "…the creation of a unique and valuable position, involving a different set of activities…" (Porter, 1998). However, if you define strategy according to Minzberg´s five P´s, then Porters' definition contains only three of the five, namely Plan, Position and Ploy, omitting Pattern and Perspective (Mintzberg, Ghoshal, Lampel, & Quinn, 2003). A slightly different approach to define strategy is that by Van den Steen, who in his paper addresses the question of what an "absence of strategy" would be characterized (Steen, 2017).

Mintzberg´s statement saying "strategy is one of those words that we inevitably define in one way yet often also use in another." (Mintzberg, 2008) demonstrates on the one hand very well

the inconsistencies and disagreements of the terminology, but is on the other hand also very worrying considering how often the term is used in crucial decisions (Hay & Peter, 1997).
Thus, a strategy consists of defining feasible objectives, defining clear actions to achieve the objectives and activating resources to implement them. In addition, it is essential that a strategy accurately describes where the company stands and how the goals set can be achieved with the available resources. (Steen, 2017) What is more, is that a strategy includes activities such as strategic planning and strategic thinking (Mintzberg, Ghoshal, Lampel, & Quinn, 2003).
The main goals of a strategy, however, is almost always the same, namely to create shareholder value (Rappaport, 1981) or to gain competitive advantage (Porter, 1998). One way to achieve this goal of value creation can be the merger or the acquisition of another company as part of an external growth strategy (Koričan, Barac, & Jelavić, 2014).

2.2.2 Growth Strategy

The key factors in keeping the competitive advantage in this fast-growing, digital and globalized world are growth strategies and the results of such strategies (Durmaz & İlhan, 2015). Within the growth strategy, there are four different strategic growth segments according to Ansoff, which are instrumentalized using the product-market matrix (1957).

- Market penetration: The company aims to grow in an established market by increasing the market share of its pre-existing products.
- Product development: The company intends to satisfy the needs of its existing market with completely innovative new products or by developing alternative product lines, variants or new product generations.
- Market development: The company is attempting to expand the target group for pre-existing products by entering new market segments or new geographical regions.
- Diversification: Product diversification requires both the development of a new product and the entering of new markets. Depending on the degree of risk tolerance, three types of diversification structure can be distinguished: horizontal, vertical and lateral diversification.

Ansoff's product-market matrix could also be divided into internal and external growth strategies (Gupta, 2012). The internal growth strategy, also known as an organic growth strategy, is one in which the company expands or grows solely with the help of internal resources and forces. In contrast, if there is a lack of internal growth opportunities, the company performs an external or inorganic growth strategy, by merging or acquiring another company (Levine, 2013). Although there are other motivations for M&As (Nguyen, Yung, & Sun, 2013) and as well another external growth strategy, namely the strategic alliance (Russo & Cesarani, 2017), due to complexity this work will not go into more detail on these.

2.2.3 Merger & Acquisition

After defining strategy and demonstrating that the M&A is part of the external growth strategy, the process will now be described in more detail. First, the terms M&A have separate definitions, with the term Merger being a fusion of two companies and the term Acquisition being a takeover of one company by another, the two terms are often seen as one. The term "M&A" as part of the external growth strategy can be further summarized as follows: "… a process in which two or more firms are combined to share their assets and resources and thus achieve common objectives, and in which the management of the two firms negotiate the terms of the deal which are then put in front of the shareholders for their approval." (Dringoli, 2016). Whilst there are several strategic reasons why a company should choose to merge or acquire another company (Reider, 2007), this work focuses on the M&A process as part of the external growth strategy due to a lack of internal growth opportunities (Levine, 2013).

At this point it should be clear, that the M&A process itself is only one part or process of a whole strategy (growth strategy), but is, however, in literature often confusingly referred to as a strategy of its own (Ogada, Achoki, & Njuguna, 2016), which underlines Minzberg's statement quoted above that the term is often misused (Mintzberg, 2008). The incorrect title of this work is, therefore, intended to be a provocation.

2.2.4 M&A Process

The entire process of a M&A can be better explained based on individual phases. Although there are discrepancies about the number of phases within an M&A (Graves, 1981) this dissertation follows the two phases approach which differs between the pre-M&A decision-making phase and the post-M&A integration processes (Haspeslagh & Jemison, 1991). These phases can then be further subdivided into the following five steps: (Evans, 2006)

Step 1 - Pre-M&A review: In the first step, the company evaluates its own situation and assesses whether a M&A is necessary or whether it is preferable to implement the growth strategy through internal resources. If a M&A is preferable, then a team defines growth criteria and develops a plan for how the M&A will proceed.

Step 2 - Search and screen targets: During the second phase of the M&A process, the search for possible target opportunities is carried out.

Step 3 - Investigation and evaluation of the target: The third phase of an M&A is to conduct a more in-depth analysis of the target company to determine whether the target company truly fits in with the acquiring company. This in-depth analysis is referred to as "due diligence", which will be discussed in more detail in the later work. Among others, the aim here is to identify possible sides for improvement, gaps in performance and best practices (Reider, 2007).

Step 4 - Acquisition through negotiation: Once the target company has been selected, the process of negotiating a M&A agreement begins. A key part of the negotiation process is a second DD, in which the target company is analyzed in much greater detail.

Step 5 – Post-M&A integration phase: After the first four phases belong to the pre-M&A phase, in the fifth phase the post-M&A phase begins, where the M&A of the two companies will be announced and the transaction completed. This is followed by the integration phase of the acquired company.

2.2.5 Key success factors for M&A

In 1999, almost 20 years ago, a study conducted by KPMG asserted that up to 83% of M&A fail and therefore don't create value (Bradt, 2015). An article in the Harvard Business Review from 2016 confirms the findings of this study with the statement "M&A is a mug's game, in which typically 70%–90% of acquisitions are abysmal failures." (Martin, 2016).

However, a new article from 2018, calls this statistic a myth and refers here to the announcement day effect, which fails to recognize the true value creation (Bradley, Hirt, Smit, & West, 2018). Although this article does not lay down a new percentage, it does state that small M&As tend to be more successful while large deals tend to fail. These statements indicate that it is indeed difficult to say whether a M&A is successful or creates value, as one often cannot see immediate success.

Irrespective of whether most M&A fail or not, the literature has several possible reasons for the failure of a M&A (Shukla, 2014), but also provides many suggested improvements to increase the likelihood of a successful M&A. One process that appears repeatedly in the literature and is crucial for a successful M&A is DD (Mullins, Thornton, & Adams, 2007) (Lajoux, 2000). The following example from an article in McKinsey Quarterly underlines this statement well: "Had the company put as much DD into that onetime figure as it did into the annual synergy target, it would have found a few relevant earlier transactions suggesting that the one-time cost wasn't likely to be less than $450 million." (Christofferson, McNish, & L. Sias, 2004).

2.2.6 Due Diligence

DD, as crucial part of the M&A process, is the careful analysis of a company to make sure that the buyer fully understands all aspects of the business that is for sale and includes the verification of the accuracy of the seller's representations, discovering undisclosed problems, and uncovering hidden assets and opportunities (Mullins, Thornton, & Adams, 2007). The objective is on the one hand to lower the risk of not creating value as well as the risk of overpaying (Goldberg & Godwin, 2001). Sinickas defines DD as "...where each party tries to learn all it can about the other party to eliminate misunderstanding and ensure the price is appropriate" (2004).

Another objective of a DD is to find an appropriate price and to identify various synergy values that can be realized by a M&A by analyzing the targets books, records and other internal reports for financial and business trends (Evans, 2006). What is more, is that a proper DD process requires detailed planning, the assignment of various experts and expert execution (Mullins, Thornton, & Adams, 2007). The execution of a DD usually begins with the target company opening a data room, which includes all the requested documents. This can be among several other financial statements, undisclosed purchase or sales commitments, related-party transactions or contracts of employment (Roche, 2002).

After all the requested documents are collected in the data room, which nowadays is often virtual, the different experts get access and will conduct their DD s. Although there are other areas of a DD s in the literature (Mullins, Thornton, & Adams, 2007) the traditional DD can be separated into FDD, CDD and LDD (Rothenbücher & Niewiem, 2008) as one can see in the table below.

Due Diligence	Focus of Enquiries	Results Sought
Financial	Validation of historical information, review of management and systems	Confirmation of underlying profit. Providing basis for valuation.
Legal	Contractual agreements, problem solving	Warranties and indemnities, validation of all existing contracts, sale and purchase agreements
Commercial	Market dynamics, target's competitive position, target's commercial prospects	Sustainability of future profits, formulation of strategy for the combined business, input to valuation

Table 2 - Main Areas of DD (Howson, 2017)

Financial Due Diligence

FDD involves detailed analysis and focuses on the economic and financial situation of a potential target company. In particular, the historical financial statements and corporate planning are examined, whereby future earnings potential is of outstanding importance for determining the purchase price. Apart from this, also the management, the employees and the information system are checked during this process. The FDD is mainly conducted by financial experts and analysts within consultancies. While the structure and content of a FDD can vary from company to company, it can be structured according to two main approaches: In the first approach, the entire financial situation of the company is analyzed retroactively. The second approach not only includes figures and financial ratios but also analyses the strategic planning within the framework of the future financial situation of the company (Howson, 2017).

Legal Due Diligence

LDD is the detailed examination of the legal situation of a potential target company. It focuses on examining the opportunities and risks of internal and external legal relationships, e.g. in the fields of company law, contract law, labor law and antitrust law. In the internal perspective, on the other hand, the legal basis for the analysis is the company law situation, structures under works constitution law and the property rights of the target company. The external perspective, on the other hand, is the review of contractual relationships with third parties, ongoing proceedings, competition law areas, environmental risks, public law relationships as well as the legal culture, which shows the company's general handling of legal issues. In addition, pending or threatened legal disputes are analyzed (Rosenbloom, 2010). These tasks form the core of a traditional LDD in a transaction. A vast majority of LDD is the verification of the availability of key elements of the business and, in addition, the lawyers are required to provide a legal opinion to the acquiring company and its management on liabilities or contingent liabilities (Harvey & Lusch, 1995).

Commercial Due Diligence

The CDD, also known as Strategic or Market DD, examines the strategic components within transactions and examines the sustainability of the target company's business model in detail. Since a M&A is about creating future value, CDD, unlike other forms of DD, estimates future performance and rather refers to information outside the company (Niederdrenk, 2017) (Howson, 2017). In addition, necessary information about competitors is obtained in order to be able to correctly assess the market environment. The structured CDD procedure is divided into four phases; project planning, collecting, processing and analyzing data, checking plausibility, and the final preparation of the report and presentation (Deloitte). Various frameworks can be used for CDD, such as Porter´s 5 Force model, Ansoff Matrix, BCG Model or the SWOT Analysis. A key element of CDD are also a variety of interviews with management, customers and experts to better understand the company, the market as well as potential competitors. Besides consultants, analysts are also frequently required to conduct CDD.

Now that the reader has enough knowledge about the management concept and understands that a successful due diligence results lead to more successful M&A, the next part will describe the technological concept.

2.3 Artificial Intelligence

2.3.1 Definition of Artificial Intelligence

One recent technology mentioned in the research of Frey & Osborne (2013) that has or will have an impact on tasks in the new world of work is AI. But before further discussing AI, for the sake of completeness a short definition of the term intelligence will follow. However, to avoid an endless philosophical debate about what the definition of intelligence is, this thesis simply confines the following definition: "Intelligence measures an agent´s ability to achieve goals in a wide range of environments." (Legg & Hutter, 2007) Whereas the question is invariably the same as how " AI " is defined, the answer to this question may vary over time. The reason for that is that the expectations of AI as well as capabilities are constantly increasing (Dignum, 2017) as technology is continuously developing. This statement is supported by in 1950 introduced Turin Test, where computer scientist wanted to show the machine's ability to exhibit intelligent behavior equivalent to, or indistinguishable from, that of a human. By definition of this test, in which a person had to decide whether a particular text was produced by a computer or a person, most computers would nowadays already be artificially intelligent (Bringsjord, 2008).

The second problem of finding a definition is that it is sometimes unclear to which type of AI one refers, since there are two different approaches, namely the weak AI, also known as Narrow AI, and the strong AI, also called Artificial General Intelligence (Franklin, 2007). Here it is also rather problematic to find an exact differentiation between weak and strong AI in the literature. In sum, however, weak AI is about mastering concrete application problems of human thinking, but is still limited to a few mostly repetitive tasks, so to say a near human-performance whereas Strong AI describes a state in which a machine is fundamentally capable of everything that a human being would also be capable of, but not better (Chopra, 2012). If one were hypothetically applying this differentiation of AI to the theories explained in the first paragraph, one could argue that Autor´s *et al.* theory (2003) is based on weak AI and Brynjolfssons *et al.* theory (2011) rather on strong AI.

There is also the hypothesis (Eden, Steinhart, Pearce, & Moor, 2013) that computers will be substantially better and/or more intelligent than humans, then a further term to describe such an AI would be needed, a so-called Artificial Super Intelligence, which won´t be part of this thesis, since this is at the moment too hypothetical (Bostrom, 2014).

However, the definition of AI has still not been clarified and is not a purpose of this dissertation. Whether referring to the definition of Simmons & Chappels stating that: "The term AI denotes behavior of a machine which, if a human behaves in the same way, is considered intelligent." (1988) or to the recommended definition of Singh Grewald: "AI is the mechanical simulation system of collecting knowledge and information and processing intelligence of universe: (collating and interpreting) and disseminating it to the eligible in the form of actionable intelligence." (2014) the fundamental problem of not even having a definition of human intelligent yet either remains.

However, based on the theory of Frey *et al.* (2013), the first definition must be viewed critically, since human behavior also covers labor and therefore the definition is ambiguous. Therefore, in this dissertation, the second definition, which was at length discussed by Professor Singh Grewal (2014), is accepted.

2.3.2 Associated Technologies

Now that a definition for the term AI has been defined, a brief overview of this technology will be provided. AI is a subfield of computer science that deals with the automation of intelligent behavior and ML (Kose, 2014). The terms "ML", "DL" and "Neural Networks" are furthermore quasi subfields of AI and form technological foundation behind AI (Kim, 2017).

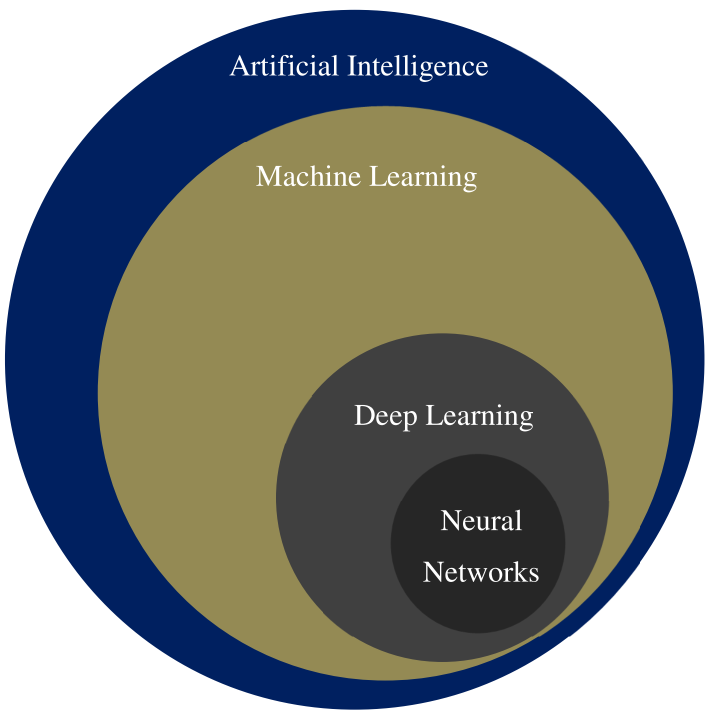


Figure 1 - Overview AI technologies

Since in the literature there is no general agreement on the classifications of the technologies and algorithms as well as its capabilities associated with the term AI (Xin, 2018), the following paragraph defines a common ground for this work.

The core technologies of AI is the learning of systems or so-called ML. **ML** describes mathematical techniques that enable a system, i.e. a machine, to independently generate knowledge from experience. ML techniques are used where the knowledge base is not sufficient to write a code, where huge amounts of data need to be scaled, where a program needs to adapt its behavior, or where the solution changes over time. ML provides the basis for many capabilities in AI, which will be discussed later in this thesis. (Mitchell & Jordan, 2015) The computer scientist Tom M. Mitchell defines ML as follows: "A computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P* if its performance at tasks in *T*, as measured by *P*, improves with experience *E*." (1997). As this definition is not immediately clear one can simplistically say that the concept behind ML describes a process in which a machine learns a specific task or procedure on its own and presents an output, without being taught before (Cooper, 2018).

There are basically three types of ML algorithms: supervised, unsupervised and reinforcement learning (Cooper, 2018) (Dasgupta & Nath, 2016) (Dey, 2016).

- Supervised learning is task-driven: the algorithm predicts a behavior or an output using labeled data and experience given by human
- Unsupervised learning is data-driven: the algorithm discovers similarities and hidden structures in unstructured or semi-structured data without any experience
- Reinforcement learning is environment controlled: The algorithm learns to respond to an environment and to adopt intelligent behaviors without given data using a trial-and-error approach to find the most optimal next step or solution.

Another part of ML is **DL**, which is currently the most popular method in the field of AI, although not broadly applied. While classical machine-learning algorithms rely on fixed model groups for recognition and classification, deep-learning algorithms independently develop these models further or independently create new model levels within neural networks. Thus, models for new events do not have to be manually developed and introduced again and again, as would be the case with classical ML algorithms (Xin, 2018). Furthermore, Neural networks are groups of algorithms that are structured according to a human brain in order to recognize recurring patterns and then to arrange or label them. Within this Neural Network there are hidden layers, which are the layers between input and output layers, whereby artificial neurons receive a set of weighted inputs, data, and through an activation function generate an output, information. It is a typical part of almost any neural network in which engineers simulate the types of activities that take place in the human brain (Guresen & Kayakutlu, 2010). Although many researchers are working on a solution, the problems with hidden layers are still that due to the very high degree of automation, it is not yet possible for humans to understand the decisions made by the machine, which is, however, necessary to fully trust its outcome (Knight, 2017).

Because DL, Neural Network and Reinforcement ML, as further developments of ML, are still emerging and have therefore not been proven to work sufficiently in practice, this dissertation exclusively focuses on the already established ML technologies, namely supervised and unsupervised ML as it is explained on page 15.

2.3.3 What makes AI so current?

The idea that human intelligence, or more generally the processes of human thinking, can possibly be automatized or mechanized, that man could construct and build a machine that shows intelligent behavior in some way, goes back to 1748, when Julien Offray de La Mettrie published his work L'Homme Machine (1748). However, it was in 1956 when John McCartney, an American computer scientist and cognitive scientist, found the first AI research workshop on the campus of Dartmouth College with the purpose of bringing together researcher with interest in automata theory, neural nets and the study of intelligence and with that imprinted the term “AI” (Russell & Norvig, 1995). In the following decades the scientific field of AI went through highs and lows, phases with high research activities alternated with years of low research activities and investments, the so-called "AI winters". Whereas the first AI winter occurred from 1974 to 1980 due to too high expectations that were not fulfilled, and the second AI winter from 1987 to 1993, due to a failure of expert systems that as well did not meet the expectations at that time. An expert system is a computer program that simulates the thinking and decision-making of a human expert in a particular field (Tan, 2016). At the same time, it quickly became apparent that the solution competencies found were sector-specific and therefore not generally applicable, so nothing else than clever programming rather than intelligence (Negnevitsky, 2001).

An early milestone of AI was the victory of IBM's chess computer Deep Blue over world champion Garry Kasparov in 1997 (McCorduck, 2004). Another milestone was when in 2016 Google's deepmind software AlphaGo defeated South Korean champion Lee Sedol 4-1 in the Chinese board game Go. But why is technology so advanced only now, even though some

prestigious AI researcher had at that time predicted that within a generation machines would be as intelligent as humans?
The following reasons, among others, are responsible for this progress (MSV, 2018) (Mitchell & Jordan, 2015).

- Big Data

The first and foremost driver of current interest and activity in the AI is the enormous amount of data that is available today and increases every second, the so-called Big Data (O'Leary, 2013). Over the past two years, 90 percent of all existing data has been generated. This huge amount of data is important for the AI as it learns from this data and can draw conclusions. While AI needs the enormous amount of data to learn and optimize itself, humans, however, need and demand AI to organize all the unstructured data to give it a sense. The more data an AI has, the better or more accurate the outcome.

- Cheap Storage

All the data produced today must also be stored somewhere to be processed later, but this would be quite expensive if the cost of storage had not drastically decreased over the years (LaChapelle, 2016). While in 1980 one gigabyte of storage did cost around $500.000, the price decrease to $0,03 today. But not only the cost of the storage has shrunk, so did the size, which makes it possible for companies to store lots of data in their own storage.

- Processing Power

Finally, to be able to process such a large amount of data in a reasonable amount of time, a very powerful and fast processor is required. Of course, such a powerful processor did not yet exist at that time when Julien Offray de La Mettrie published their work nor when John McCartney found his workshop.

Besides Big Data, the further decreasing costs for storage and the Processing Power, there are also technologies like the Cloud Storage and 5G as the fifth generation of mobile communications that push the increasing trend for AI.
However, everything has a limit, which means that although storage is getting cheaper, it cannot be for free of charge as well as the speed of processors will eventually cease to rise exponentially (Guba, Nanai, & George, 2017).

2.3.4 Capabilities

This part of the work reveals and explains the capabilities that can or could be achieved with those current technologies. Although in the literature there are eight capabilities, this work only describes those capabilities which are first, already in use today and, second, which rely on either supervised or unsupervised ML.

These eight capabilities can generally be divided into two categories, those that capture information from unstructured data and those that process these informations further. However, since the capabilities that process information further, are not yet mature enough for the market, only Information capturing capabilities will be explained in this dissertation, including the NLP, the so-called clustering and the information extraction (Burgess, 2018). Those capabilities are for the reader to understand as these build a foundation for solutions in the DD Process.

Information Capturing Capabilities:

- Information Extraction

Information extraction is the capability to extract structured information from unstructured or semi-structured machine-readable documents. In most cases, this activity involves the processing of human language texts using NLP. For informational extraction is mostly based on supervised ML algorithm (Tang, 2008).

- Natural Language Processing

NLP is a hypothetically driven range of calculative techniques for analyzing and representing naturally texts at one or more levels of linguistic analysis in order to achieve human-like language processing for a range of tasks or applications (Liddy, 2001). NLP is based on the basic idea that any form of language, spoken or written, must first be recognized. Important is not only the single word but its context with other words, whole clauses or issues. However, since language is a very complex system of symbols, both supervised and unsupervised ML algorithms are being used (Behzadi, 2015).

- Clustering

Clustering refers to the process of grouping a set of entities in a way that entities belonging to the same group are more related to each other in a certain way that entities belonging to other groups (Ghuman, 2016). Simply put, the computer is given a large amount of unstructured data, and it automatically finds patterns within the data set using unsupervised ML. Clustering is particularly interesting for Big Data, as it is becoming increasingly impossible for humans to extract valid information from the stuffed data sets.

The reader should now know enough about the underlying theory, the management and the technical concept for the following analysis.

3. CHAPTER: METHODOLOGY

The first part of this dissertation provided the theoretical basis for the study and is based on secondary literature, such as academic articles, journals and specialist books. In the second part, primary data was captured which was, besides secondary data, used for the analysis.

In order to obtain primary data for answering the research questions, interviews were chosen as a method of qualitative research. Especially in guideline-based interviews, neither formulation nor sequence is subject to a rigid and binding sequence and the possible answers are largely open (Gläser & Laudel, 2004).

The interview questions were formulated based on knowledge obtained from secondary literature. Regarding the interviews, since the traditional DD process can be divided into three different areas, namely legal, financial and commercial, and there are already AI-based solutions for the DD, at least one expert from each topic was chosen to be interviewed. The interviewees were mainly identified by searching for keywords on Linkedin or were contacted directly through companies. In addition to the field of work, a requirement was that the interviewees are knowledgeable about AI or even be computer scientists. Furthermore, the 10 interviews were conducted in the most international scale as possible to cover the most relevant global markets. What is more, among the professionals of the interviewees are management consultants, lawyers, analysts or board members of AI tool providers.

After each of the 10 phone interviews, the notes taken were summarized while the essential content was retained and in then evaluated with the help of the summary content analysis according to Mayring (2000). The evaluation was guided by the research questions, the managerial and technical concept described in the and literature review.

The following table shows the 10 experts, their country of origin, their field of profession and the acronym used for the following analysis. The summaries of the interviews can be found in Appendix 2.

Acronym	Name	Country of origin	Field of Profession
Expert 1	Ravi Arora	India	CDD
Expert 2	Shravan Manghani	India	CDD
Expert 3	Chris Hunt	United Kingdom	CDD
Expert 4	Aurimas Racas	Japan	FDD
Expert 5	A. A.	Switzerland	CDD
Expert 6	Lachlan Vogt	Australia	FDD

Expert 7	Dayo Famakinwa	America	DD
Expert 8	Franz Kögl	Germany	AI Tool Legal
Expert 9	Thomas Cheung	Singapore	AI Tool Legal
Expert 10	Madhu Nagaraja	Canada	AI Tool Commercial

Table 3 - List of Experts

Since the interviews are mainly designed to answer the research questions, a framework was developed to test the underlying theory from Brynjolfsson *et al.* (McAfee & Brynjolfsson, 2011). The framework relies on the Task Model by Autor *et al.* (2003) explained in the first part of the literature review. However, for the theory to be tested, this model had to be adapted to each single due diligence process as well as to artificial intelligence. After the basic framework for each individual due diligence was built with the knowledge from the secondary literature, experts were asked to fill in typical tasks of the due diligence they are working in. After all the tasks had been collected, the list was again given to experts, who then had to assess the individual tasks based on their own expertise. While the definitions of routine and not routine tasks were given and explained what manual and cognitive tasks are, AI was not limited to ML as it is done in this dissertation.

4. CHAPTER: ANALYSIS AND DISCUSSION

After the data has been collected and analyzed with the qualitative content analysis according to Mayring (2000), in the following chapter the results from the expert interviews will be presented.

The analysis is structured as follows: First, all the problems and trends of the different DD are collected and described. Subsequently, all the advantages of AI cited by the interviewees are analyzed and compared with results from tests conducted by AI tool providers. In the third part, three existing solutions are introduced to illustrate what is already technically possible with machines today. Finally, reasons for the no adoption or slow adoption of AI in the DD process are presented. These reasons or rather barriers and can be clustered into implementation reasons, including technological and financial reasons, and utilization reasons, including liability and trust. Since the word machine was often used in the interviews as a synonym for an AI-based software tool, this expression is also used in this thesis. into ecological and technical reasons as well as pessimistic and averse reasons.

4.1 Due Diligence

LDD Trends & Problems

In the last few years, according to the interviewees, in LDD a number of problems did arise due to a few recent trends. The first trend that arose, is that M&As have become increasingly international and therefore more complex (Expert 5).

One problem that followed with that, are language barriers between the law firm and the target company, which did not exist in the LDD to such an extent before. The second problem that resulted from this, is that in different countries there are also different legislations and jurisdictions which also increasingly complicate proper LDD (Expert 9).

A second inescapable trend is that with the economies growing and companies expanding, more business and deals are made, followed by contracts and documents, which need to be reviewed during LDD (Expert 5, Expert 9).

This increasing workload, combined with the third trend, a higher expectation for more detailed and in-depth research, results in a much higher time pressure during the DD process. (Expert 5) Time pressure is the main problem in DD nowadays (Expert 5, Expert 8).

According to one interviewee, the task of reviewing documents manually nowadays takes up to 90% of the total M&A Process time, therefore fewer sophisticated verification tasks can be performed (Expert 9). Consequently, to save time, a law firm often skips some parts of documents and trusts that the unviewed documents are fine, which is, however, a huge risk. This statistic must be viewed critically, as it comes from an expert from an AI Tool who tends to speak in favor of his solution, which, however, does not mean it is wrong.

The other problem caused among others by time pressure is a lack of accuracy (Expert 5). When going through documents manually as quickly as possible, important paragraphs can be overlooked or important points could be missed (Expert 7, Expert 8). Given that the law firm is liable for every element of the conducted DD, it is particularly important not to miss out any point, as otherwise high costs from lawsuits could arise (Expert 5, Expert 7).

Nowadays, an increasing number of law firms can carry out LDD. Because of this increasing supply, the price for a DD will fall, which in turn has consequences for quality, time and comprehensiveness of a DD.

FDD Trends & Problems

The problems occurring in LDD were not mentioned by any of the interviewees of the FDD. Neither the number of financial documents reviewed in the DD process has changed significantly in recent years, (Expert 4) nor has time in which the FDD is conducted. One reason for this is, again among others, that many analysis are already being supported by software tools such as Excel, which saves time and at the same time allows the processing of a lot of information (Expert 4).

However, according to some interviewees, one issue with any FDD is that due to the differences between the companies and their ERP systems, all the data found in the data room at the beginning of the DD is unsorted and incomprehensible to the management consultant performing the DD. The issue is, that the sorting and understanding of this data takes a lot of time since it is done manually (Expert 3, Expert 4, Expert 6). What is more, is that during this process a constant contact with the company manager or an employee from the target company is crucial (Expert 5, Expert 6). Once the data has been understood, it can be classified correctly and processed further.

Besides this problem, there are other tasks mentioned by the interviewees, which also require a lot of time, but which were not discussed in more detail during the interview. However, same as in LDD, the trend of increasing demand for a deeper and more sophisticated analysis becomes increasingly important in FDD as well. To obtain such deeper and more meaningful result, FDD tasks are being combined with results from other DD (Expert 3, Expert 4).

An example, one interviewee named, was that instead of just looking at geographical sales of one subsidiary, as one would do in the traditional FDD, now a consultant is also interested in the drivers behind the financials or the behavior of the customer of this geographical location, which was not the case in the past (Expert 4).

CDD Trends & Problems

According to the interviewees, some problems which exist in the LDD can also be found in the CDD. One problem that overlaps with the LDD is that the manual execution of the various tasks takes a very long time since each DD is very case-specific and all processes must be set up again and again from scratch (Expert 10).

The biggest challenge, however, is the data collection. Although it is already possible today to buy sophisticated industry analyses as well as customer data from various providers a lot of data still must be collected manually, which is time-consuming and costly (Expert 1, Expert 2). A further problem with manual execution, is like in the LDD, that things can easily be overlooked or data can be missing (Expert 1). The result is often that erroneous and wrong conclusions can easily be drawn.

The trend that applies to all DD is the growing demand for a more sophisticated result. As was the case with FDD, today CDD also takes results from other analyses to improve the results and can make more statements (Expert 4). To obtain a more meaningful result, big data can be used, which was repeatedly discussed in the interviews. In DD, Big data has the advantage of having information that could not previously be obtained using classic data collection methods. At the same time, however, one has to be careful here because biased information can quickly lead to wrong conclusions (Expert 1, Expert 3).

4.2 Advantages of AI

After finding out that there are problems in traditional DD such as time, accuracy, language and cost, the following paragraph collects the advantages of AI mentioned by the interviewees. The main advantage mentioned by almost all interviewees was that AI is faster than a human being (Expert 5, Expert 7, Expert 8, Expert 10). The second most frequently mentioned advantage of a machine is accuracy (Expert 3, Expert 7, Expert 8, Expert 9). That tasks can be completed faster and more precisely using a machine supported by AI is also proven by the two tests, attached in the appendix. The first test showed that the lawyer assisted by a machine called DiligenceEngine was up to 60% faster in processing contracts and able to find all the important clauses instead of only 58%. In addition, the second test showed that an AI tool called Geeklaw compared to lawyers was, even without working together with a lawyer, 9 % more accurate when looking through contracts and needed only 26 seconds instead of 92 minutes. Although the two results are very dissimilar and are from AI Tool providers, so they need to be seen critically, both confirm that with the assistance of a machine or even through the machine alone, the process is faster and more accurate.

What is more, a machine can read documents in different languages, which is again a huge advantage in the increasing internationalization of M&As, mentioned as a problem (Expert 9, Expert 10).

Furthermore, although one might expect that the promised speed and accuracy of a machine would make a machine less expensive than a human the experts, however, more or less shared the view that this is not necessarily the case (Expert 3, Expert 4, Expert 7). Reasons for this were that it always boils down to what tasks the machine would substitute or what position the employee had that was replaced by a machine. Only one of the interviewees believed that a machine would be cheaper, however only under the preconditions of standardized data, which will be explained later (Expert 3).

4.3 AI-Tools

The following section presents a selection of current AI tools for DD. The activities, the technologies, and the advantages are described. It is striking that almost all AI tools on the market are active in LDD, as this area seems to have the greatest potential or need on the market. Though there are still a handful more providers for LDD, only Luminance and Intrafind were willing to be interviewed. Furthermore, it can be said that the LDD providers are very similar in their technologies and solutions so that these two providers already cover a major part of the market. What is more, is that one AI tool is presented that was not created directly for CDD, but can nevertheless be used for this purpose.

Luminance

The company Luminance describes itself as a leading platform for pattern recognition and AI in the legal field. Luminance reads and understands contracts and other legal documents in any language and finds relevant information and irregularities without instructions. No training or adjustment is required and the system can be used on the first day.

The following added values are promised to customers:

- Find hidden risks:

Luminance identifies potential risks in the data room without any instructions. Unusual contracts and clauses are tracked down and classified to find missing or inconsistent information.

- Faster, Accurate Review

Efficiency and effectiveness are increased by up to two thirds. The system reads and understands thousands of contracts, clauses, documents and other relevant information.

Although Luminance is mainly based on unsupervised ML, it must still partially use supervised ML technologies. Especially important for a good result are the Capabilities Clustering and NLP.

IntraFind

IntraFind develops products and solutions for the efficient search, finding and analysis of structured and unstructured information considering all relevant data sources of a company.

The main product of Intralink is the iFinder, which is an AI-based solution for the analysis of texts. The iFinder also includes a software solution called Contract Analyzer, which is particularly relevant for DD. This ML-based software uses, among other technologies, NLP to assist with the LDD in analyzing contracts, creating red-flag reports, performing initial or in-depth analyses, and providing a document- and clause based view of contract documents.

This allows, among other features, a faster comparison of documents or clauses in the LDD process. What is more, is that Intrafind claims, that with their software 20 - 25 % of the basic legal reading work is no longer necessary. The next step of Intrafind will be the evaluation and analysis of contracts, which are still performed by lawyers.

DDIQ

DDIQ is a risk-based cognitive computing platform that combines automation with the skills of a human researcher to uncover and analyze the regulatory risks of a subject that are not found using current techniques. Although DDIQs objective was to empowers compliance teams at financial institutions, Corporations, and investment firms to mitigate risk constantly by screen all available public data about a subject, it can also be used for CDD.

Based on supervised and unsupervised ML, and using clustering as well as NLP DDIQ takes unstructured public data about a company and its directors, and analyzes them by keywords to give a comprehensive overview of a target and its directors. This, however, is performed within a very short period of time. The interviewee explained that if you take all public data, such as blog entries and news articles, or even reports about directors that exist about Microsoft in America, and feed those into the machine, it will only take about 20 minutes to get an overview of the most critical issues about the company instead of days or weeks. In addition, not only are analyses of a company possible on a daily or weekly basis, but these are also available in 15 different languages.

DDIQ can be useful in CDD in the way that the task of data collection about the target company can partially be substituted as well as the extraction of important information from this data.

4.4 Reasons against adoption of AI in DD

After having analyzed the problems and trends of the various DD, shown which advantages AI brings and what existing providers offer or promise, the question arises why both, law firms and consultancies, have not yet or yet only partially implemented AI in their DD.

The following part analyzes the arguments given by the interviewees as to why there is either none or only a slow adoption of AI has in DD. The reasons named by the experts can basically be divided into two categories, namely implementation and utilization. Whereas the first category consists of mainly technical and economical reasons, the second category of reasons of trust and liability.

Implementation Reasons

The implementation reasons are better described as barriers since the use of AI is intended but simply not possible today and can be roughly divided into technical and financial reasons. (Expert 5).

The first argument for the slow implementation of AI is the unstandardized nature of the data (Expert 3, Expert 4, Expert 6). As already known from the secondary literature, at the beginning of a DD the various divisions of the target company are asked to place the data requested by the law firm or management consultancy in a data room which is nowadays often virtual. This data room can then be accessed by the company consultant or the law firm carrying out the DD. However, since the data is neither sorted nor adapted to a standardized format by the various departments, the first hurdle for the implementation of AI arises. For a machine to work properly, it needs data in a standardized format that the machine can understand and read (Expert 4, Expert 5). In addition to the barrier that the data from the various departments is transferred to the data room in a company-specific format, a second barrier also arises from the fact that the data is also unsorted. Unsorted in this case means that the data in the data room has been stored without any label and is therefore completely incomprehensible to someone who is not working in the target company. At the same time means that if no one external understands the data, no machine can be trained to process them further (Expert 3).

Contrary to these two barriers, the company Luminance promises to identify unusual contracts and clauses in the data room already without any adjustment of the data to the machine. But since Luminance is a LDD software provider and legal contracts are more likely to be standardized than for example books of accounts, this promise needs to be seen critically as it could apply only to certain contracts or clauses.

So, for the lawyer or consultant to be able to understand the data, it must be sorted. This, however, is only possible with constant communication with the manager or with employees of the target company, which leads to the third hurdle of the adoption of AI, namely the necessity of communication. Interpersonal actions such as dialogue are not yet possible with machines today (Expert 5). On the other hand, it must be said that if the second hurdle is overcome, meaning that the data is sorted, the third hurdle also no longer applies.

The next issue mentioned during the interviews is that it takes a tremendous amount of time to train a machine to the point where it performs a task better than a human (Expert 7). FDD, for example, consists of thousands of individual tasks, which means that it is not economically viable to program a machine for each individual task for both cost and time reasons (Expert 6). Although in the interviews the costs were not mentioned as an advantage of AI, costs, as the next hurdle, still matter for minor tasks and make the substitution by a machine redundant. Since the amortization period considered for a machine is medium to long-term, many processes, however, e.g. in the FDD process, are classified as short-term and you would have to train the machine always again on the particular targets companies data, the substitution of such small tasks is, therefore, inefficient (Expert 6).

The last barrier is, although this is especially true for LDD, that there is still too little data to train a machine properly (Expert 5). If a company to be merged with or acquired is small, then often there are too few contracts and documents to train the machine to the point where it is better and more efficient than a human. That the basis for a well-functioning AI is a massive amount of data, was also already stated in the literature review. However, this problem should be less in the FDD and CDD, because there is a certain amount of data available (Expert 6).

Utilization Reasons

Whereas the reasons analyzed above were that it is technically and financially not yet possible to implement AI, the following part analyzes reasons for not using AI in general, even if adoption would be possible.

The most important reason given by the interviewees is the trust in a machine. As already mentioned in the literature, the decisions of a machine cannot yet be understood by humans and are therefore a black box (Knight, 2017). With this lack of knowledge, an implementation of a solution based on AI in DD is still being viewed very doubtfully. What is more, is that AI, in general, has not yet been successfully established and proven to work, so that it is still risky to implement. Apart from that, it is also a major cultural step to let a machine do important tasks and people first would have to be willing to take this step. (Expert 1, Expert 10).

Moreover, the subject of liability is a big issue as well in DD, since, as already mentioned earlier, a law firm or a management consultancy is responsible for all its actions and thus also for all the results of a machine, so it must be 100 % sure that all the actions are performed correctly and these actions need to be traceable by humans as well (Expert 5, Expert 8).

So, until a machine cannot prove that it is better than human and the actions are not traceable, no trust can be created in AI, and neither can any responsibility be taken for it. Even more, the big cultural shift of Machines doing tasks only a human was able to do must be overcome.

5. CHAPTER: CONCLUSION

5.1 Main Findings & Conclusions

AI is a topic that has been around for a very long time but has only recently become increasingly popular again due to the factors described in the literature. Furthermore, it is often claimed that AI will have a major impact on the working environment and will either support or even replace a vast number of jobs. However, it is not yet known, due to a lack of studies, which specific sectors or branches will be affected by AI. Due to this lack of studies on this specific topic, this research has taken the initiative and has analyzed the impact of AI on the Due Diligence Process, as most as the decisive process of the M&A.

The following section closes this knowledge gap by linking the two fields of AI and DD using knowledge gained from literature as well as from the analysis. Subsequently, the theoretical and practical implications of the results are described to critically reflect on the study and to limit the framework for future research.

RQ 1: What are the main problems in the traditional way of doing DD *and can these problems potentially be solved by* AI*?*

Irrespective of the type of DD, with semi-structured interviews, it was possible to identify problems in the way some traditional DD are currently carried out today. The main problems found in the analysis were time, human error, language, too many documents, and costs. In addition to problems, trends were also identified in the analysis. One of these trends is an increasing demand for ever more sophisticated and deeper DD results. To achieve these in-depth results, another trend has emerged of linking the results of the different DD in order to draw better conclusions.

Overview	
Main Problems	Advantages AI
1. Time pressure 2. Human error (Accuracy) 3. Languages 4. Cost 5. Too many documents	1. Speed 2. Accuracy 3. Multilingual 4. Cheaper (under preconditions) 5. Ability to process many data

Table 4 - Overview DD & AI

To further answer the question, if these problems could potentially be solved by AI, a list of the various problems of the DD have been compiled and contrasted with the advantages of DD. Comparing the current problems of DD with the advantages of AI a great correlation can be observed. Based on this correlation, it can, therefore, be concluded that in traditional DD there is definitely potential for the implementation of AI. It could even be argued that there is an actual need for implementing AI to keep up with trends.

RQ 2: What added value do the AI tools bring compared to the traditional DD?

Based on the benefits anticipated by the interviewees, the promised improvements of the providers of AI tools as well as the results of the attached test, it can be said that some tasks of the DD process can be done in less time and more accurate through AI. With this time being saved, it is possible to perform other tasks which in turn improve the whole DD process. Also, the fact that the machine is able to analyze documents in different languages is a big advantage and saves a lot of work.

However, as already discussed in the analysis, it is not possible to say that tasks can be performed more cost-effectively using AI, as this requires a few prerequisites that are currently not met. Here it depends very much on which tasks are replaced or how high the salary of the replaced person is.

RQ 3: Are there companies that already offer AI-based solutions for the DD *solutions, how do the solutions look like and which problems do they solve?*

There are already companies that offer solutions based on AI, but most of them are only designed for LDD and are still very young. Most solutions offer the lawyer support in contract analysis to find specific clauses or risks. During the interviews, however, it was also agreed that these systems, although an effective tool for increasing efficiency, will not replace a lawyer. The lawyer's activity and work will continue to be relevant to an M&A transaction and will be even more efficient due to the time saved. (Expert 8)

Another tool that has been described supports CDD and helps to assess the risks of a company within a very short time based on public data. What is more, is that looking at the task models for the CDD process, one can see that there are also already more tasks that can be replaced by AI in the CDD process.

Therefore, it can be stated that the current solutions are primarily concerned with the problems of time and accuracy and mostly address the LDD.

RQ 4: For which types of DD *can AI offer the greatest benefit?*

At the moment, the LDD has the greatest potential to benefit most from AI. The reasons for this is, that currently most of the problems in the traditional DD exist in the LDD. Hence it can be assumed that there is not only demand but rather a need for innovation.

A look at the advanced task models, on the one hand confirms that there is a lot of potential in LDD, but shows on the other hand, that there is the same potential in the future in CDD. For both frameworks, the experts claimed that within the next 5-10 years all tasks would be partially or completely substituted by AI. (Appendix 6, Appendix 8)

RQ 5: Which AI technologies and capabilities are being used by these companies?

Most solutions are based on both supervised and unsupervised ML technologies, with some being based more on one rather than the other. Luminance, for example, is based mainly on unsupervised and less on supervised ML and with Intrafind it is the other way around. Nevertheless, both solutions are based on the same technology. The same applies to capabilities, that actually all solutions mainly rely on NLP, clustering and further rule-based algorithms which are not detailed in this thesis.

RQ 6: Are there AI-based solutions already offered for all three DD*? If not, which are the reasons?*

No, only in the LDD and the CDD are solutions based on AI offered today. The main barriers for no or the slow adoption of AI in the FDD and party CDD, are the unstandardized nature of the data in the dataroom, the time it takes to train a machine, the essential communication with the target, the trust in the results of a machine as well as the huge cultural change. The reasons are explained in more detail in the last part of the analysis.

However, by looking at the task frameworks, experts are optimistic that over the next few years these barriers will be overcome and there will be solutions offered in every DD. (Appendix, 6, Appendix 7, Appendix 8)

RQ 7: Based on the findings, will AI now/ within the next 10 years have an impact on the DD *process and how much?*

To get back to the main topic, first of all, one can conclude that, yes, AI has and will have an impact on traditional DD and thus indirectly on the M&A process. Whereas some tasks are being substituted partially, others are being substituted fully by AI in every DD Process. The biggest impact due to AI at the moment is on LDD, for which there are already first solutions. However, as already said, when the barriers of the other DD will have been overcome, there is also going to be a huge impact on the CDD and the FDD as well.

How much impact AI will have on the DD can be seen by looking at the single DD task frameworks attached:

LDD: (Appendix 6)

The Legal Task Model confirm that with already 38 % of the task substituted by AI, the impact of AI on LDD is currently the greatest. Furthermore, it can be seen that the lawyer's cognitive tasks will only be partially replaced by AI, whereas many simpler tasks will be replaced fully. This again affirms the statement that the lawyer will not be replaced and he will even have more time to devote to more difficult tasks, such as analysis, and the outcome of the LDD will be more comprehensive.

FDD: (Appendix 7)

Despite the fact that at present there are no FDD tasks supported by AI, it is stated that within the next 10 years 87% of all FDD tasks are substituted either partially or entirely by AI. What is noticeable, however, is that in contrast to the other DD, 13% of the tasks performed in FDD cannot be substituted by AI, neither now nor in the next years. The reasons for this is that these two tasks are the most judgmental and the most deal-specific ones in the FDD and therefore broad knowledge is needed, which is however hard to be replaced by AI. (Expert 4)

CDD: (Appendix 8)

Having a look at the commercial task framework and comparing it with the AI-tools offered on the market for CDD, which is only one, the current impact on the CDD process is, however, greater than anticipated as there are already a quarter of the tasks partly supported by AI. In addition, it is claimed by the expert that within the next 5-10 years all CDD tasks will be partially or completely replaced, whether it is routine, non-routine, manual or cognitive.

Bringing all the frameworks together, it can be concluded that in the next 10 years 96% of all tasks in traditional due diligence at Howson (2017) will be substituted by AI. More precisely, 62% of the traditional due diligence is substituted partially and 34% of it fully. However, it must be mentioned that these statements were made purely on the basis of the assessments of three experts and therefore offer a trend rather than correct statistics. Nevertheless, in closing, it can be said that AI is going to have an impact on the due diligence process.

5.2 Theoretical validation

Based on Brynjolfsson´s underlying theory (2011), the advanced DD task models allow some conclusions to be drawn. First, the theory that non-routine tasks as well as routine tasks can be reinforced by computer or AI can be supported. Furthermore, it can also be shown that both manual and cognitive tasks can be partially or completely replaced. This means that the theory can also withstand individual processes such as the DD process.

5.3 Managerial Implications

Now that it is known that AI will have an impact on the DD process, companies that are currently conducting DD without AI-based solutions must prepare for change. In the following paragraph, using the Kotter's 8-step change model, employees and executives will successfully be prepared for implementation of AI in the organization. This work provides a good basis for many steps.

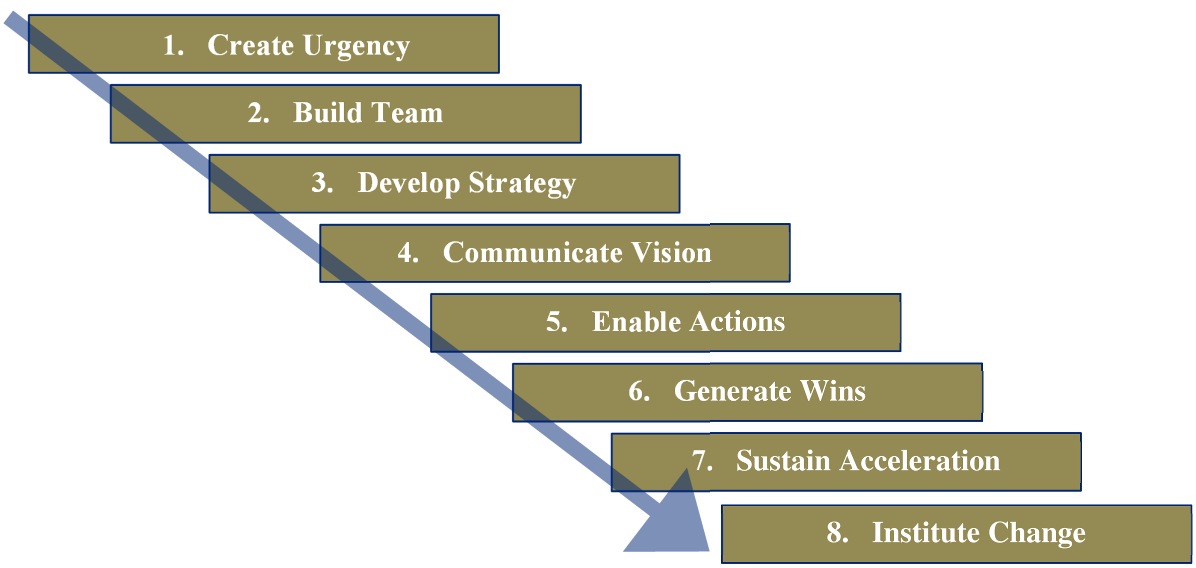


Figure 2 - Kotter's 8-step change model

The first step is to create an awareness of the urgency of change among both managers and employees. This work has shown that AI will have an impact on any DD in the future, so everyone involved in the process should be conscious of it. The second step is to put together a leadership team, preferably from different departments and with different competencies, that supports the change and is willing to drive it forward.

The third step is to create a strategy that clearly expresses where the company currently stands in the DD process and what needs to be done to be perfectly adapted to an AI supported DD in the future. This strategy should also include that for the implementation of AI the company requires employees with programming experience, very fast processors and a basic understanding of the employees to deal with a large amount of data and to ask the customer in a certain way. In the fourth step, the impact of AI must be explained through reports and meetings, as well as prepared through workshops and training. In addition, it should be communicated in detail through meetings that only a few jobs are replaced and even most are simplified and improved by AI.

The fifth step is to look at the exact status quo of a company and eliminate organizational structures, workflows and routines that could slow down the change. It can be helpful to have an external consultancy to identify these organizational structures.

It should be avoided to set costly and time-consuming goals for the beginning, but rather to define quickly achievable intermediate goals in the sixth step. These goals could include the successful completion of employee training or the introduction of new processors.

The seventh step is to give feedback to the employees and show how prepared the company already is for an implementation of AI. In addition, employees should also be brought up to date on the market for AI tools. The last step is to integrate this change and the acceptance of the employees and executives into the corporate culture. Not only should the company communicate internally, but also externally, to be prepared for the change. This gives both the employees a more confident feeling about their job as well as for the company a competitive advantage if other companies are not yet as prepared.

5.4 Limitation

The following part describes imitations regarding the approach as well as the results obtained in this dissertation. As qualitative research enables a certain degree of discretion in the analysis of results. It is important to note that in this dissertation a possible bias in the selection of participants that influences the reliability of the results can be found due to convenience sampling in the interview process. Furthermore, it must be pointed out that the motivation of the described M&A, although others exist, is limited to the growth of the company and includes only one buyer and one seller.

Moreover, it should be considered that this work insists on statements from only 10 interviewees, which makes it difficult to state with certainty that the outcomes of this research are comprehensive and complete. Furthermore, because of the small sample size, it is not possible to design a perspective that accurately reflects the company internally; for this purpose, several employees of a company would have to be interviewed in various positions. However, investigating this would go beyond the scope of this thesis.

In addition, the small sample size of interviewed AI solutions does not reflect the entire market, which means that the conclusions drawn must be viewed critically.

Also, the frameworks of the DD which have been created by the researcher and derived from the task model require some points to be mentioned which add to the limitation. On the one hand, the basic framework was created purely from the knowledge from secondary literature and on the other, the years included were set to 5-10 years solely on the basis of a statement by one interviewee. Additionally, since the results of the frameworks, including tasks and estimations of the tasks, are each based on one expert each, this will not allow the results to be concluded with absolute certainty.

5.5 Further Research

Since this work has shown that AI has and will have an impact on the M&A process, this work provides an interesting impetus for further research. One point where further research is needed, based on the statement that most transactions fail, is whether with AI there will be less M&A transaction that fail. For the clarification of this question, it is recommended to use a quantitative method. A complication, however, would be that due to the still very young AI tools, only little data is available for quantitative analysis, so that there is a risk that the results would not be meaningful or significant.

In addition, it is interesting to find out, although the opposite is stated by the experts, whether in the long run costs can be reduced with AI in the DD. A long-term study using a quantitative approach, which is still very difficult at present, is recommended to test this.

As this paper only briefly addressed the topic of acceptance and trust in a machine, it is also suggested to check to what extent the AI tools would be accepted by the clients. It would be useful to conduct a broad survey with employees involved in the M&A process.

One last interesting research in this area would also be to test the impact of AI in other phases and steps of the M&A process. An example would be in phase 1 of the M&A process, where a suitable company is being searched for.

REFERENCE LIST

Ansoff, I. (1957). Strategies for Diversification. *Harvard Business Review*.

Autor, D., Levy, R., & Murnane, R. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*.

Behzadi, F. (2015). Natural Language Processing and Machine Learning: A Review. *International Journal of Computer Science and Information Security*.

Bostrom, N. (2014). *Superintelligence: Paths, Dangers, Strategies.* Oxford University Press.

Bradley, C., Hirt, M., Smit, S., & West, A. (2018). Research Shows That Smaller M&A Deals Work Out Better. *Hardvard Business Review*.

Bradt, G. (2015). *83% Of Mergers Fail -- Leverage A 100-Day Action Plan For Success Instead.* Retrieved from www.forbes.com: https://www.forbes.com/sites/georgebradt/2015/01/27/83-mergers-fail-leverage-a-100-day-value-acceleration-plan-for-success-instead/#4b146b035b86

Bresnahan, T., Brynjolfsson, E., & Hitt, L. (2002). Information technology, workplace organization and the demand for skilled labor: firm-level evidence. *The Quartely Journal of Economics*.

Bringsjord, S. (2008). The logicist manifesto: At long last let logic-based artificial intelligence become a field unto itself. *Journal of Applied Logic*.

Brown, N., & Sandholm, T. (2018). Superhuman AI for heads-up no-limit poker: Libratus beats top professionals. *Science Magazine*.

Burgess, A. R. (2018). *The Executive Guide to Artificial Intelligence.* Springer.

Chopra, R. (2012). *Artificial Intelligence.* S. Chand Publishing.

Christofferson, S. A., McNish, R., & L. Sias, D. (2004). Where mergers go wrong. *McKinsey Quarterly*.

Cooper, S. (2018). *Machine Learning for Beginners.* PublishDrive.

Dasgupta, A., & Nath, A. (2016). Classification of Machine Learning Algorithms. *International Journal of Innovative Research in Advanced Engineering*.

Deloitte. (n.d.). *www2.deloitte.com*. (Deloitte) Retrieved from www2.deloitte.com: https://www2.deloitte.com/de/de/pages/finance/solutions/Transaction-Advisory-Services.html

Dey, A. (2016). Machine Learning Algorithms: A Review. *International Journal of Computer Science and Information Technologies*.

Dignum, V. (2017). Responsible Artificial Intelligence: Designing AI for human values. *ITU Journal: ICT Discoveries*.

Dringoli, A. (2016). *Merger and Acquisition Strategies: How to Create Value.* Edward Elgar Publishing.

Durmaz, Y., & İlhan, A. (2015). Growth Strategies in Busınesses and A Theoretical Approach. *International Journal of Business and Management*.

Eden, A., Steinhart, E., Pearce, D., & Moor, J. (2013). *Singularity Hypotheses: An Overview.* Springer Verlag.

Evans, M. H. (2006). *Excellence in Financial Management*. Retrieved from exinfm: www.exinfm.com

Franklin, S. (2007). A Foundational Architecture for Artificial General Intelligence.

Frey, C., & Osborne, M. (2013). The future of employment: How susceptible are jobs to computerisation? *Quartlerly Journal of Economics*.

Ghuman, S. S. (2016). Clustering Techniques- A Review. *Journal of Computer Science and Information Technology*.

Gläser, J., & Laudel, G. (2004). The Expert Interview and Content Analysis. *Forum: Qualitative Social Research*.

Goldberg, S., & Godwin, J. (2001). Your Merger: Will It Really Add Value? *The Journal of Corporate Accounting & Finance*.

Grant, R. M. (2016). *Contemporary Strategy Analysis.* John Wiley & Sons.

Graves, D. (1981). Individual reactions to a merger of two small firms of brokers in the re-insurance industry: A total population survey. *Journal of Management Studies*.

Guba, T., Nanai, L., & George, T. (2017). Physical Limits of Computation. *Journal of Quantum Information Science*.

Gupta, P. K. (2012). Merger and Acquisitions: The strategic concepts for the nuptials of corporate sector. *Innovative Journal of Business and Management*.

Guresen, E., & Kayakutlu, G. (2010). Definition of artificial neural networks with comparison to other networks. *Science Direct*.

Harvey, M., & Lusch, R. (1995). Expanding the nature and scope of due diligence. *Journal of Business Venturing*.

Haspeslagh, C., & Jemison, B. (1991). Managing acquisitions. Creating value through corporate renewal. *New York: The Free Press*.

Hay, M., & Peter, W. (1997). Good Strategy: the view from below. *Elsevier Science Ltd, 30*(5).

Howson, P. (2017). *Due Diligence: The Critical Stage in Mergers and Acquisitions.* Routledge.

Jordan, M., & Mitchell, M. (2015). *Machine learning: Trends, perspectives, and prospects.* sciencemag.org.

Keller, G. (2008). The Influence of Military Strategies on Business Planning. *International Journal of Business and Management*.

Kim, P. (2017). *MATLAB Deep Learning: With Machine Learning, Neural Networks and Artificial Intelligence.* Apress.

Knight, W. (2017). AI Winter Isn´t coming. *MIT Technology Review*.

Knight, W. (2017). The Dark Secret at the Heart of AI. *MIT Technlogy Review*.

Koričan, M., Barac, Z., & Jelavić, I. (2014). Impact of Related Acquisition Strategy on Bidding Company Performance. *Journal of Economic and Social Studies*.

Kose, U. (2014). *Artificial Intelligence Applications in Distance Education* . IGI Global.

LaChapelle, C. (2016). The cost of data storage and management: where is it headed in 2016. *Datacenter journal*.

Lajoux, A. R. (2000). *Art of M and A Due Diligence.* McGraw Hill Professional.

Legg, S., & Hutter, M. (2007). A Collection of Definitions of Intelligence. *Frontiers in Artificial Intelligence and Applications*.

Levine, O. (2013). Acquiring Growth. *Journal of Finance*.

Liddy, E. (2001). *Natural language processing.* Encyclopedia of Library and Information Science.

Martin, R. L. (2016). M&A: The One Thing You Need to Get Right. *Harvard Business Review*.

Mayring, P. (2000). Qualitative Content Analysis. *Forum: Qualitative Social Research*.

McAfee, A., & Brynjolfsson, E. (2011). Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irre- versibly transforming employment and the economy. *MIT Sloan Management* .

McCorduck, P. (2004). *Machines Who Think.* A K Peters, Ltd.

McShane, M. (2017). Natural Language Understanding (NLU, not NLP) in Cognitive Systems. *AI Magazine*.

Mettrie, J. O. (1748). *L'homme Machine*.

Mintzberg, H. (2008). *Strategy Safari: The complete guide through the wilds of strategic management.* Canada: Pearson Education Canada.

Mintzberg, H., Ghoshal, S., Lampel, J., & Quinn, J. (2003). *The Strategy Process: Concepts, Contexts, Cases.* Pearson Education,.

Mitchell, T. M. (1997). *Machine Learning.* Tom M. Mitchell .

Mitchell, T., & Jordan, M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*.

MSV, J. (2018). *www.forbes.com*. Retrieved from Here Are Three Factors That Accelerate The Rise:Of Artificial Intelligence: https://www.forbes.com/sites/janakirammsv/2018/05/27/here-are-three-factors-that-accelerate-the-rise-of-artificial-intelligence/#366fd0dfadd9

Mullins, T., Thornton, B., & Adams, M. (2007). The Role Of Due Diligence In The Business Valuation Process. *Journal of Business & Economics Research.*

Navigli, R. (2018). Natural Language Understanding: Instructions for (Present and Future) Use. *International Joint Conference on Artificial Intelligence.*

Negnevitsky, M. (2001). *Artificial Intelligence A Guide to Intelligent Systems.* Addison Wesley.

Nguyen, H. T., Yung, K., & Sun, Q. (2013). Motives for Mergers and Acquisitions: Ex-Post Market Evidence from the US. *Journal of Business Finance & Accounting*.

Niederdrenk, R. (2017). *Commercial Due Diligence.* Haufe Lexware Verlag.

Ogada, A., Achoki, G., & Njuguna, A. (2016). Effect of Merger and Acquisitions strategies on financial performance of financial services sector. *International Journal of Finance*.

O'Leary, D. E. (2013). Artificial Intelligence and Big Data. *IEEE.*

Oxford English Dictionary. (n.d.). *Oxford English Dictionary.* Oxford.

Platt, E. (2018). Global M&A activity hits new high. *Financial Times.*

Polanyi, M. (1966). The Tacit Dimension. *Doubleday Press.*

Porter, M. (1998). What is Strategy. *Harvard Business Review*.

Rappaport, A. (1981). Selecting Strategies That Create Shareholder Value. *Harvard Business Review*.

Reider, R. (2007). Questioning M&A. *The Journal of Corporate Accounting & Finance*.

Roche, R. P. (2002). A Winner's Guide to M&A Planning. *The Journal of Corporate Accounting & Finance*.

Rosenbloom, A. H. (2010). *Due Diligence for Global Deal Making.* John Wiley & Sons.

Rothenbücher, J., & Niewiem, S. (2008). Due Diligence: Think Operational. *A.T. Kearney, Inc.*

Russell, S. J., & Norvig, P. (1995). *Artificial Intelligence A Modern Approach.* Englewood: A Simon & Schuster Company.

Russo, M., & Cesarani, M. (2017). Strategic Alliance Success Factors: A Literature Review on Alliance Lifecycle. *International Journal of Business Administration.*

Shukla, D. R. (2014). Review of Major Companies Merger Failures in The First Decade of 21st Century. *International Journal of Enhanced Research in Management & Computer Applications*.

Simmons, A., & Chappell, S. (1988). Artificial Intelligence definition and practice. *IEEE Jounal of Oceanic Engineering*.

Singh Grewal, D. (2014). A Critical Conceptual Analysis of Definitions of Artificial Intelligence as Applicable to Computer Engineering. *IOSR Journal of Computer Engineering*.

Sinickas, A. (2004). How To Do Due Diligence Research. *Strategic Communication Management*.

Steen, E. V. (2016). A Formal Theory of Strategy. *Management Science*.

Steen, E. V. (2017). Strategy and the Strategist: How It Matters Who Develops the Strategy. *Management Science*.

Strauss, A., & Corbin, J. (1994). Grounded theory methodology. *Handbook of qualitative research*.

Tan, C. (2016). The Application of Expert systems: A Review of Research and Applications. *ARPN Journal of Engineering and Applied Sciences*.

Tang, J. (2008). *Emerging Technologies of Text Mining: Techniques and Applications.*

Tzu, S. (500 BC). *The Art of War.*

Vergidis, K. (2008). Business Process Analysis and Optimization: Beyond Reengineering. *IEEE*.

Xin, Y. (2018). Machine Learning and Deep Learning Methods for Cybersecurity. *IEEE Access*.

APPENDICES

Appendix 1 - Definitions of Task Measures from the 1977 dictionary of occupational titles

APPENDIX 1: DEFINITIONS OF TASK MEASURES FROM THE 1977 DICTIONARY OF OCCUPATIONAL TITLES

Variable	DOT definition	Task interpretation	Example tasks from *Handbook for Analyzing Jobs*
1. GED Math (MATH)	General educational development, mathematics	Measure of nonroutine analytic tasks	Lowest level: Adds and subtracts 2-digit numbers; performs operations with units such as cup, pint, and quart. Midlevel: Computes discount, interest, profit, and loss; inspects flat glass and compiles defect data based on samples to determine variances from acceptable quality limits. Highest level: Conducts and oversees analyses of aerodynamic and thermodynamic systems . . . to determine suitability of design for aircraft and missiles.
2. Direction, Control, Planning (DCP)	Adaptability to accepting responsibility for the direction, control, or planning of an activity	Measure of nonroutine interactive tasks	Plans and designs private residences, office buildings, factories, and other structures; applies principles of accounting to install and maintain operation of general accounting system; conducts prosecution in court proceedings . . . gathers and analyzes evidence, reviews pertinent decisions . . . appears against accused in court of law; commands fishing vessel crew engaged in catching fish and other marine life.
3. Set Limits, Tolerances, or Standards (STS)	Adaptability to situations requiring the precise attainment of set limits, tolerances, or standards	Measure of routine cognitive tasks	Operates a billing machine to transcribe from office records data; calculates degrees, minutes, and second of latitude and longitude, using standard navigation aids; measures dimensions of bottle, using gauges and micrometers to verify that setup of bottle-making conforms to manufacturing specifications; prepares and verifies voter lists from official registration records.
4. Finger Dexterity (FINGDEX)	Ability to move fingers, and manipulate small objects with fingers, rapidly or accurately	Measure of routine manual tasks	Mixes and bakes ingredients according to recipes; sews fasteners and decorative trimmings to articles; feeds tungsten filament wire coils into machine that mounts them to stems in electric light bulbs; operates tabulating machine that processes data from tabulating cards into printed records; packs agricultural produce such as bulbs, fruits, nuts, eggs, and vegetables for storage or shipment; attaches hands to faces of watches.
5. Eye Hand Foot Coordination (EYEHAND)	Ability to move the hand and foot coordinately with each other in accordance with visual stimuli	Measure of nonroutine manual tasks	Lowest level: Tends machine that crimps eyelets, grommets; next level: attends to beef cattle on stock ranch; drives bus to transport passengers; next level: pilots airplane to transport passengers; prunes and treats ornamental and shade trees; highest level: performs gymnastic feats of skill and balance.

Source: U. S. Department of Labor, Manpower Administration, *Handbook for Analyzing Jobs* (Washington, DC, 1972).

Appendix 2 - Summary Interviews

Expert 1

19.11.2018

Ravi Arora – Growth Strategy & Due Diligence Consultant

Vizry Group – Commercial DD

New Delhi, India

Commercial DD

Vizry Group is a Management Consulting firm assisting startups to fortune ranked clients, worldwide, with a mission to vet, validate and implement growth strategies. What is more, is that based on the statement that 4 out of 6 of the commercial DD steps could be supported by AI, the company is planning to reveal AI Tools next year, which will support the decisions-making Process of a company and speed up the Commercial Due Diligence Process. The problem in DD when done manually is, that there are always elements that one misses as well as the time it takes to conduct a DD.

The solutions the company is currently working on will be based not only on Machine Learning but also on Deep Neural Networks, which is not yet properly established in the market. In addition to the classic commercial due diligence, the search for a suitable company should also be simplified, so that the machine can find exactly the right target for a buyer. According to Vizry Group, however, the problem with Commercial DD is to get access to the market data, whereby in future there will also be providers who sell exactly the data that is needed for such solutions. Even today, fewer and fewer interviews are being conducted with customers at CDD and these customers are more likely to be found on Facebook or Twitter.

Expert 2

23.11.2018

Shravan Manghani – Computer Scientist & Due Diligence Expert

Mumbai, India

Commercial DD

Shravan Manghani is a Computer Scientist and Due Diligence Expert working as an Business Analyst at CreditCheck Partners in Mumbai. Although there are no AI-based solutions yet for Commercial DD and everything is done manually, there will be solutions in the future supported by supervised machine learning. The first huge advantage this brings is that the time during the DD will be decreased and second, that the machine takes decisions without any bias. Regarding costs, although one might think that the DD will be cheaper with AI, it always depends on how long it takes to adapt or program the machine to the company and who you replace with the machine, whether that person is expensive or not. However, the machine itself is not expensive and can be covered within around 2 project and will come down to zero, but need to be adapted or trained to the company in the DD process.

Expert 3
17.11.2018
Chris Hunt – Head of M&A and Divisional Board member
Rentokil Initial Plc.
United Kingdom
Commercial DD

Rentokil argues that although in recent years, due to the large amount of data generated, traditional due diligence problems have arisen, the data and the way companies work are too different to train a machine to do so. In addition to the large differences between companies and their data, the quality of the data also decreases due to the ever-increasing size of the data. Big Data will change the commercial DD, but so far it is and remains difficult for AI to transform this amount of data into a usable result. Machines need to be trained and can then replicate a task over and over again.
But in a transaction it is also very likely that one won't always find the same kind of data that the machine can process, and then you would spend more time programming and less time doing the due diligence. Furthermore, in due diligence, communication with the vendor is still very important to understand the quality and value of a business.
However, if you have a standardized dataset, the machine is better, cheaper and more accurate, but this is not the case today. In the future, AI will change due diligence in such a way that a link can be made between different DDs, replacing repetitive tasks and thus achieving a better and more qualitative result.

Expert 4
22.11.2018
Aurimas Racas - Senior Manager at Transaction Advisory Services Ernst Young Japan
Financial DD

Ernst & Young supports many companies in M&A transactions and carries out both Financial Due Diligence and Legal Due Diligence. The company claims to be the most technically advanced auditor on the market. At Ernst & Young, the topic of artificial intelligence is becoming more and more interesting and often comes up for discussion. And due to the ever-increasing amount of data, one could assume that the application of artificial intelligence in financial due diligence will also increase, but this is not yet the case. With the financial DD one cannot speak of Big Data either, since the amount of data in the financial area has always been available, which is why the demand for Artificial Intelligent has also not increased much, since there are already tools that perform many tasks which are however not based on AI. Nevertheless, due diligence is changing in the sense that nowadays a financial DD is becoming increasingly deeper and complex. One example is that instead of just looking at sales geographically, financial DD is now interested in the respective customer, which was not the case in the past.
For the financial DD EY does not yet use an AI based tool, because it is difficult to define single tasks in the financial analysis to code them as it is the case for example with the legal DD, where you have the repetitive task of going through contracts. Nevertheless, EY has run a few pilot projects to come up with solutions for, for instance, identifying "one offs", where machine management read reports and search for specific keywords. Other solutions for tasks that EY is not yet working on, but which could be automated, would be data cleaning or price folding analysis, which takes a lot of time and is often repetitive. The purpose of data cleansing is to understand data from the company from different divisions and with different information in order to be able to classify them correctly. This task can often only be performed with the help of a company manager. However, solving the problem with ML is very difficult as it is impossible to create a uniform model for different companies. In addition, you need to be 100% accurate when cleaning data, but today the machine can only do 80%.
What could be supported by AI in the near future, however, would be simple analyses, such as identifying debt items or outliers. In general, however, there is still not much demand for

AI-based solutions in the financial DD, since another problem is that you need a lot of standardized data for the DD to train the machine, but this is not the case with a DD. When a company's data is collected for the transaction, it usually consists of random excel extracts. Apart from that, the ERP standards are different in all companies, so you have to talk to the company over and over again to understand the data. This unstandardized data and the need of a communication make an AI-based solution impossible at the moment. But what is changed with the ever increasing amount of data and the demand for ever more extensive analysis is the DD process as it is performed today. The financial DD will no longer be limited to the financial DD, but will rather be combined with the commercial DD as well as the operational DD to better understand and make more sense out of the financial results. So this increasingly complex and difficult process will also increase the demand for ML and statistics and therefore AI.

So AI cannot help in the traditional way of doing a financial and commercial DD, but in the future modern way. In the future, you will insert data sets into a machine and this will tell you at which points in a company you need to have a closer look and people will have more time for more complex issues. An example of this is when two coffee distributors of the same location wanted to merge. In a horizontal merger such as this, logistical synergies are particularly important. In the past, financial DD would have simply made sales analyses of different locations and not looked at whether they could support each other. Such commercial DD analyses, which were not feasible at that time, are now possible and make DD more complex and therefore better. So it can be said that AI improves DD in the sense that the whole financial and commercial DD process becomes more sophisticated and many tasks are taken over or supported by machines so that people whose processes are replaced have more time for new tasks.

Advanced Task Model:

LinkedIn:

You stated that the two tasks "Provide inputs to the sales and purchase agreement (SPA) on additional representations and warranties" and "Estimate potential synergies post-transaction" won´t be substituted by AI in the next 10 years. Can you explain why?

It's because these two areas are the most judgemental and the most deal-specific ones. When it comes to reps and warranties, you basically need to know "everything else" about the deal to be able to provide inputs. For synergies, you need to be aware of the strategic rationale of the transaction and what management plans to do after the deal to know what to even start with. So these two areas require broad knowledge and are very situation specific - and thus I think hard to be replaced by AI

Expert 5
21.11.2018
A. A. – Partner
A. Law Firm Switzerland
Legal DD

The firm is one of the leading M&A law firms in Switzerland and has not yet implemented tools based on Artificial Intelligence. The main reason for this is the sheer size of the Swiss market. Although today's AI tools learn quickly and only require a few contracts to achieve a satisfactory result, when doing a legal DD the law firm in Switzerland has too little data from the target company, so that it is not worth programming and training a machine to the point until a good result is achieved. It takes too much time to train and program the machine to the contracts of the target and if one would carry out this task classically, thus manually, today he is still quicker. Another current problem is that in electronic data rooms in Switzerland, the data records often consist only of images and therefore cannot be read correctly by the machine. Apart from that, Legal DD still often has to communicate with the customer because data is not available or some data is not understandable.
However, the law firm is confident, that once the software currently available has proven itself and trust has been established in such tools, that AI-based software will be implemented for the legal DD in Switzerland. The reason for this is on the one hand that the machine performs the tasks that today are performed faster, but also much more precisely than it is possible for a junior lawyer today. Apart from the reliance on the machine, the demand for AI tools will increase in the future, as the legal due diligence has changed in the sense that there are more and more law firms that are able to perform a due diligence and with a increasing supply, the DD Process will be offered cheaper, but with a lower quality as well. AI should be able to help with this development of but it is not worth using AI until you have reached the level of a human with a machine. Artificial intelligence must therefore be used to meet the simultaneously increasing demands of customers to carry out a DD ever deeper.

However, this will not happen until the machine is not as good or better than the human, because at the end of a DD the firm is liable for the outcome and therefore must be 100% sure to have carried it out correctly.

In addition, as the number of companies purchased from foreign countries is increasing, transactions become more international and complex, resulting in more documents to be checked in the due diligence and to more language barriers. However, the compatibility of different AI tools and whether each firm in different countries needs the same tool must still be examined for such complications.

Expert 6
16.11.2018
Lachlan Vogt - Manager & Artificial Intelligence Expert
Accenture
Australia
Financial DD

The artificial intelligence that is already possible today is called Narrow AI or weak AI, where the machine must be trained with a large amount of training data for each individual task. However, due diligence can be divided into thousands of individual tasks and to replace due diligence with AI one would have to write a separate program for each of them. For some tasks it might make sense and the machine would complete the task better than a human, for others it would be the contrary. Sorting data is a task that still takes a lot of time in the financial Due Diligence could be supported by Artificial Intelligence. One problem could be, that when sorting and understanding data, communication with a company manager is highly important, which makes it harder to replace the process.

However, there are algorithms that use Natural Language Processing to read documents and then mark and cluster them, but the data is often too different, so it is not worth it. In addition, the amortization period of AI based solutions is often medium to long term, but an M&A DD only takes 6 months, so the implementation is not worthwhile in terms of time and cost. Another problem with the implementation of AI solutions is that there are too few qualified people to program AI based solutions for each process of an DD.

Expert 7
30.11.2018
Dayo Famakinwa - Group Product Manager at Merrill Corporation
Greater Minneapolis – America
Merrill Corporation

Merrill Corporation is a provider of a virtual cloud-based data room for due diligence and plans to implement AI in your solution. So, if a company want to be sold, they want to explore all the options they have. The company will reach out to several investment banks and pick one that is the best choice. The investment bank then does a market analysis with potential buyers and sorts those out, which are not a good fit to buy this company. Once they come up with a final list of companies, they start officially the Due Diligence, which also involves starting a data room. If an investment bank is involved in the Transaction, then one employee from the investment bank organizes the data room and gives out the data the buyers need to value the selling company.

This process of getting all the data and sorting this data from the sell side is a very time consuming task and therefore has potential to be substituted by AI. What is more, is that if you have a huge company being sold, the amount of documents and contracts you have is radicicolous and manually finding a " red flag" or a "finding" is not efficient. What is more, is that with doing this manually you run the risk of missing out important information that could potentially hurt the acquisition and you want to find this as quickly as you can. Nowadays it is possible to train a AI system to analyze document specific data, but one needs a lot of historical data to be accurate. But we are not yet at the point, where the Machine can task on its own for the DD, it still needs human interaction.

A lot of companies that are buying a company get an insurance, because at the moment it is not possible to check all the information, so you cannot be 100 % sure, the company you are buying is worth what the documents checked disclosed.

If there will be AI used in Due Diligence Process, it will be more accurate than a human and be much quicker, but not directly cheaper, because the lawyer that you can substitute with AI has time to do different things, so he won't be excluded. However, the more accurate the Due Diligence is, the less is the likelihood of lawsuits after the transactions, which can save a lot of money and cost for insurance.

Expert 8
13.11.2018
Franz Kögl – CEO
Intrafind
Legal DD Tool

Mr. Kögl is a member of the board of Intrafind, a company based in Germany and one of the leading providers of text analysis and search solutions. The main product of Intralink is the iFinder, which is an artificial intelligence based solution for the analysis of texts. The iFinder also includes a software solution called Contract Analyzer, which is particularly relevant for due diligence. This machine learning based software uses, among other technologies, Natural Language Processing to assist with the legal DD in analyzing contracts, creating red-flag reports, performing initial or in-depth analyses, and providing a document- and clause based view of contract documents. This allows, among other features, a faster comparison of documents or clauses in the Legal DD process.
One of the main problems with Legal DD is the effort required to obtain a precise overview of deal breakers in a relatively short period of time. Once the buyer has made the requested data available in a data room, it has to be checked as quickly as possible whether, for example, special "change of control" clauses or special termination rights would make a purchase unprofitable or impede it. Carrying out this step manually, one is under great time pressure and may easily overlook or miss important points. These manual routine tasks are to be supported or replaced by the Contract Analyzer, since it can more quickly and more accurately read these documents. From experience it can be said that with the software 20 - 25 % of the basic legal reading work is no longer necessary, which however does not mean that it is cheaper because this depends on the lawyers who would carry out the work instead. The Contract Analyzer uses not only supervised and unsupervised ML, but also rule-based, linguistic and ontological procedures to identify clauses and data points in contract texts, extract and process them, and finally automatically analyze the key information. Problems arise when the machine is unable to read the documents as a result of incorrect scanning or poor quality. In addition, it is not yet possible to scan handwritten documents. The machine has no problem if terms are misspelled or are in German/English.
However, in the Legal DD, the machine will not replace the lawyer's review tasks because it only refers to clauses and does not legally review them. In the future, however, the machine will also replace these reviewing tasks, as the time advantages and accuracy of the machine

have great advantages. Also the characteristics of the machine being neutral, and therefore not biased and able to work continuously, are advantageous.

Finally, it can be said that the machine has a great advantage for the Legal DD, however, humans cannot be replaced and will not be replaced in the near future.

Expert 9
21.11.2018
Thomas Cheung – Legal Product Expert
Singapur, Asia
Luminance – Legal DD Tool

The company Luminance considers itself to be the leading platform for pattern recognition and artificial intelligence in the legal field. In contrast to other AI based providers, Luminance is mainly based on unsupervised learning and can therefore be used directly at the beginning of the DD without instruction and therefore does not have to be trained beforehand, which can sometimes take days or weeks. Furthermore, Luminance, unlike other providers in Legal DD, is not a clause extraction tool, but identifies potential risks in the data room without any instruction. Unusual contracts and clauses are detected and classified by Natrural Language Processing and then clustered to find missing or inconsistent information and therefore differ from classic clause extraction tools. What is more, is that different languages as well different legislations are no longer a problem with Luminance- The problem within Legal DD, which is to be solved by this software, is that the number of documents that need to be gone through in the DD is overwhelming and this manual work can take up to 90% of the M&A process.

Through Luminance it is possible to reduce this time of Legal DD by up to 50%, and what junior lawyer did before is now supposed to be done by the machine. Additionally, the machine is much more accurate than humans and, unlike before, it can go through all the company's contracts instead of some and one doesn't have to trust the contracts that weren't done manually are alright.

According to the "Customer Case Study M&A Due Diligence" (Luminance, 2016, p. 1-2), in which the Norwegian law firm BA-HR used the Luminance tool, a time saving of at least 33% was achieved. The system was also able to check contracts in Norwegian.

For the Italian law firm Portolano Cavallo, Luminance reviewed and extracted 700 documents for M&A deals in Italian, English, French and German and identified various clauses to be deleted or added. According to Portolano Cavallo, Luminance has helped to process large-scale M&A transactions much more efficiently, allowing lawyers to focus on higher quality work (Luminance, n.d., p. 1-2).

Expert 10
08.12.2018
Madhu Nagaraja – Product Manager DDIQ
Toronto – Canada
Commercial AI-Tool

DDIQ is a risk-based cognitive computing platform that combines automation with the skills of a human researcher to uncover and analyze regulatory risks of a subject that are not found using current techniques. Although DDIQs objective was to empowers compliance teams at financial institutions, Corporations and investment firms to mitigate risk constantly by screen all available public data about a subject, it can also be used for commercial DD.
The problem with commercial due diligence is that it takes a very long time to obtain data and this data is then often not up-to-date or too few. The reason why it takes so long is that commercial due diligence is very individual because you need unique data, to understand the specific market and customers.
DDIQ takes all the public data about a company and it directors, and analyzes them to give within a very short period of time a comprehensive overview of a target and its directors. With DDIQ, this target screening is not only cheaper, but way faster and much more accurate than the traditional way of consultants going through news, reports or blogs. With DDIQ, for example, it is possible to take all the information about Microsoft in the USA or Portugal and feed it into the machine, and after only 20 minutes you have an overview of the company. This process could have taken days or weeks before DDIQ was introduced. Now the consultant only needs to do a request. The machine here refers to certain keywords that are defined before the analysis. To function properly, the company had access to several data banks in specific geographical locations and was able to read documents in 15 different languages. The technologies used were among others, NLP, clustering, therefore supervised as well as unsupervised Machine Learning. Another advantage using DDIQ is that a target company can be screen on a daily or weekly basis, to keep one updated.
However, the trust in such software had to be established, because using such AI-based tools is a huge cultural shift.

Appendix 3 - Diligence Engine Test

Traditional vs. Computer-Aided Due Diligence

What is the best way to review contracts for due diligence or contract management purposes?

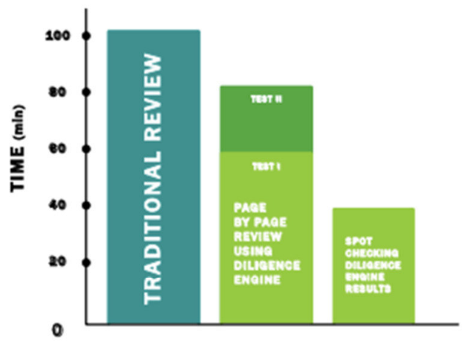
Today, most contract review gets done by junior lawyers reading contracts page by page. This process is time consuming and prone to human error. We think we've built a better way to do this work. Our software reads contracts for user-specified provisions (e.g., change of control, assignment, term), puts its findings into summary charts, and includes workflow tools to help users refine this information.

How would a lawyer using it stack up against one reviewing contracts the traditional way? We tested it out. Here's what we found:

An experienced lawyer using **DiligenceEngine was significantly faster and more accurate** than an experienced lawyer doing diligence the traditional way.

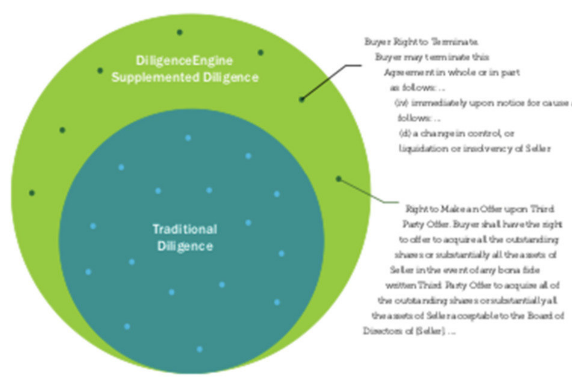
SPEED

The system-user completed the review in **20–30% less time** even when he still read-through every agreement and close to **60% less time** when he only spot checked system results. Both ways were more accurate than traditional review.



ACCURACY

The system identified a number of significant change of control clauses the non-user missed, including a termination-on-change-of-control provision. In one test, the non-user identified **7 of the 12** substantive change of control provisions the system user got (and nothing the system user missed).



Testers

* **DiligenceEngine user Noah** ***(our co-founder & CEO)***	* **Non-user "Tom"**
* **4 years as a corporate associate at a top international law firm, 2.5 years at DiligenceEngine**	* **3 years as a corporate associate at a top international law firm, 3 years in-house at a financial services company**
* **2006 NYU J.D.**	* **2006 top ten law school J.D.**

1

Test I

Ten agreements (about 330 pages total)

Provisions Covered: title, parties, date, term, assignment, change of control, governing law, *exclusivity, most favored nation, non-competition, non-solicitation* (*italicized* provisions not yet covered by system).

Why review for provisions not covered by system? DiligenceEngine does not yet cover every provision potentially needed in a review. However, we add new provisions over time and the system includes workflow tools to improve manual review. This test partially measured whether the system would help on uncovered provisions.

Speed:
Tom took 236 minutes to review all contracts. Noah, aided by the system and reading every document page by page, completed his review in 159 minutes.

Accuracy:
The system and Noah caught a termination on change of control provision Tom missed:

> [Buyer] Right to Terminate.
> [Buyer] may terminate this Agreement in whole or in part as follows:
> ...
> (iv) immediately upon notice for cause as follows:
> ...
> (d) a change in control, or liquidation or insolvency of [Seller]

Tom did not find any substantive provisions the system or Noah missed.

Test II

Six agreements (about 270 pages total)

Provisions Covered: title, parties, date, term, assignment, change of control, amendment, governing law.

Speed:
Tom completed his review in 100 minutes. Noah reviewed the documents page by page in 81 minutes. A few hours later, Noah reviewed the same documents a second time, primarily targeting speed. In this review, he only spot checked system results and deleted false positives. He finished in 41 minutes.

Accuracy:
Both times Noah went through the agreements, he and the system found 12 clear change of control provisions. The non-user found seven. Here's one of the provisions Tom missed:

> Right to Make an Offer upon Third Party Offer. [Buyer] shall have the right to offer to acquire all the outstanding shares or substantially all the assets of [Seller] in the event of any bona fide written Third Party Offer to acquire all of the outstanding shares or substantially all the assets of [Seller] acceptable to the Board of Directors of [Seller]. ....

General characteristics: All agreements reviewed were fresh to both reviewers and the DiligenceEngine system. They were US law governed contracts sourced from EDGAR. Reviewers completed templates that had been provided in advance. Reviewers had reasonable disagreements on some provisions; only clear and substantive provision misses were discussed above.

Potential Limitations of Results

- Noah reviewed the same documents twice in Test II. While he did not change any findings of his initial page by page first review (or look back at it) once it was completed, his speed on his second review may have been faster because of his familiarity with the documents.
- Both Tom and Noah were significantly more experienced than typical contract reviewers. Less experienced reviewers would likely be slower and less accurate.
- Since this was only a one-on-one test, it is possible that some portion of observed differences could be due to variations in the reviewers themselves.
- A typical diligence review project could have reviewers working for much longer and later. Human error is likely to increase in such a situation, which should increase the benefit of using DiligenceEngine.

We intend to run follow-up studies addressing these limitations.

Details on DiligenceEngine

DiligenceEngine reads contracts for user-specified provisions (e.g., change of control, assignment, term), puts its findings into summary charts, and includes workflow tools to help users refine this information. Users can download summaries (in Word or Excel) or manipulate and store them online. The software reviews contracts in seconds per page, and finds 90% or more of nearly every contract provision it covers (as tested on a diverse set of contracts).

How the Provision Extraction System Works

The system processes agreements in all common electronic formats, including raw scans. Once uploaded to the system, agreements are first run through Optical Character Recognition review (if needed) and then passed through our provision models. Findings are put in summary charts.

We use advanced methods to build provision models. We feed large numbers of provision examples into customized training algorithms which consider this mass of data and build probabilistic provision models. These go far beyond keyword searches.

PROVISIONS COVERED

DiligenceEngine covers the provisions that come-up most frequently on M&A due diligence projects.

The system currently finds the following provisions:

Title, Parties, Date, Term, Assignment, Change of Control, Confidentiality, Amendment, Indemnity, Notice, License Grant, Bankruptcy, Governing Law

New provisions are added regularly. And custom provision models can be prepared on request.

SETUP

The software is available installation free via the cloud, or can be hosted locally. It is intuitive enough to use with little or no training.

OUR CO-FOUNDERS

Noah Waisberg, our chief executive, was previously a corporate associate at Weil, Gotshal & Manges LLP, where he focused on M&A and securities law.

Alexander Hudek, our chief technologist, holds a Ph.D in computer science from the University of Waterloo with a focus in machine learning and logics.

LEARN MORE

Website: **https://diligenceengine.com**
Email: **info@diligenceengine**

DiligenceEngine

Appendix 4 - LawGeex Test

HOW RESULTS WERE CALCULATED

To mark the tests, consultant Christopher Ray ultimately measured the participants' performance based on three metrics:

- **False Negative** – an issue was missed
- **False Positive** – an issue was misidentified
- **True Positive** – an issue was accurately identified

This was then used to create three final metrics:

- **Recall:** how many topics were accurately spotted in the right place out of the total number of topics possible to detect. As a standalone measurement, recall is insufficient as it allows one to achieve the maximum score through guesswork.
- **Precision:** measures the number of correct answers made against the number of total answers given.
- **F-measure:** the final accuracy score is the harmonic mean between Precision and Recall, calculated as follows:

$$\frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}}$$

Following two months of testing, the LawGeex Artificial Intelligence achieved an average **94% accuracy rate**, ahead of the lawyers who achieved **an average rate of 85%**.

On average, it took 92 minutes for the lawyer participants to complete all five NDAs. The longest time taken by a lawyer to complete the test was 156 minutes, and the shortest time to complete the task by a lawyer was 51 minutes. In contrast, the AI engine completed the task of issue-spotting in 26 seconds.

The AI engine achieved 100% accuracy in one of the contracts. The highest individual score for a lawyer on a single contract was 97%.

THE RESULTS AND FINDINGS

	NDA 1	NDA 2	NDA 3	NDA 4	NDA 5	AVG
Lawyer 1	83%	92%	88%	79%	88%	86%
Lawyer 2	85%	92%	86%	81%	93%	87%
Lawyer 3	85%	72%	80%	79%	81%	79%
Lawyer 4	61%	58%	74%	76%	65%	67%
Lawyer 5	93%	90%	93%	94%	93%	92%
Lawyer 6	89%	90%	94%	97%	90%	92%
Lawyer 7	74%	81%	86%	84%	91%	83%
Lawyer 8	93%	84%	90%	90%	95%	91%
Lawyer 9	62%	80%	81%	73%	57%	70%
Lawyer 10	84%	94%	82%	88%	89%	88%
Lawyer 11	87%	82%	83%	87%	82%	84%
Lawyer 12	65%	67%	70%	69%	55%	65%
Lawyer 13	76%	67%	72%	71%	73%	72%
Lawyer 14	95%	92%	91%	97%	91%	93%
Lawyer 15	92%	94%	95%	97%	89%	94%
Lawyer 16	95%	97%	94%	97%	92%	95%
Lawyer 17	88%	92%	81%	89%	91%	88%
Lawyer 18	81%	86%	85%	88%	78%	84%
Lawyer 19	97%	94%	95%	97%	91%	95%
Lawyer 20	97%	93%	90%	94%	81%	91%
LAWYER AVG	84%	85%	86%	86%	83%	85%
LAWGEEX	92%	95%	95%	100%	91%	94%

Appendix 5 - Luminance Customer Case M&A Due Diligence

Luminance

CUSTOMER CASE STUDY: M&A DUE DILIGENCE

BA-HR

BAHR

Time spent on document review reduced by over 33%.

Key result

Business background

BA-HR is a leading Norwegian business law firm. Founded in 1966 and based in Oslo, much of the firm's practise in transactions and dispute resolution has a multi-jurisdictional and multilingual aspect.

Early adoption of Luminance

The firm started using the first release of Luminance's artificial intelligence platform for contract review as part of its transactional due diligence analysis and reporting at the end of 2016.

Explaining the reason for his firm's adoption of the technology, BA-HR partner Svein Gerhard Simonnæs says "AI tools carry the potential for huge improvements in efficiency of document analysis and reporting. Think about it as going from the Stone Age to the Iron Age. Every good law firm and every good lawyer will want this kind of tool."

BA-HR deployed Luminance as an on-site appliance which plugged into the firm's existing secure data environment. Lawyers could begin using the platform via their web browsers with little instruction, thanks to Luminance's intuitive interface.

"Luminance proved extremely useful even as a first pass at the data room," says Simonnaes. "It sorted contracts into 'buckets' that our team could use to determine which subsets of documents were important and which were not."

> "Luminance will appeal to the most ambitious and talented lawyers."
>
> **Svein Gerhard Simonnæs, Partner, BA-HR**

Supervised machine learning enabled Luminance to automatically tag clauses within English-language documents, such Change of Control and Assignment clauses. Issues uncovered throughout the review could be annotated and categorised by the team, enabling better communication of potential negotiation points.

Norwegian-language clause were easily labelled by the team where they appeared within documents. Luminance's machine learning algorithms then instantly uncover all other occurrences of the clause throughout the data room.

"Once you're in a project, very little effort is needed to put Norwegian-language clauses into the right bucket," says Simonnaes. "The recognition of patterns of language across the data set is instantaneous. Luminance carries what is has learned to the next data set it sees, correctly labelling future examples of the same clauses."

Benefits

Simonnaes estimates that the time spent on legal document review alone was cut by at least one third, due to faster, more focused navigation of the data set. Collaboration tools further improved efficiency, so that more time could be spent on higher-value activities such as analysis and advising the client.

BA-HR is now rolling Luminance out to be used on all relevant due diligence assignments in parallel with clause and document type labelling in the Scandinavian languages.

"Ultimately, Luminance helps us to get to the all-important judgments faster," concludes Simonnaes. "It's a massive, massive saving of a lawyer's time, and I am confident that Luminance will raise the bar for how document review is done in every law firm."

Appendix 6 - Advanced Task Model Frameworks – Legal Due Diligence

LDD								
Task	Routine Task/ Non-Routine Task		Manual Task/ Cognitive Task		Substantially or Fully substituted by AI			
	Routine Task	Non-Routine Task	Manual	Cognitive	Now	Partially in 5-10 years	Fully in 5-10 years	Never
Collection of target data	X		X				X	
Sorting target data		X	X		X		X	
Checking correctness/ completeness of data	X		X		X		X	
Extraction of important clauses	X			X	X		X	
Clustering contracts		X		X	X			
Analysis of all documents to clarify whether the company has been built in compliance		X		X		X		
Analysis of all documents relating to transactions and company acquisitions		X		X		X		
Analysis of all contracts which are of essential importance for the company		X		X		X		
Analysis of pending court cases and chances of litigation		X		X		X		
Analysis of employment contracts		X		X		X		
Identification of red flags	X			X	X		X	
Examination on the availability of all licenses	X		X				X	
Evaluation of target value / Acquisition prize		X		X		X		
13 tasks in total	5 (38 %)	8 (62 %)	4 (30 %)	9 (70 %)	4 (38 %)	6 (46 %)	6 (46 %)	0 (0 %)

Appendix 7 - Advanced Task Model Frameworks – Financial Due Diligence

FDD								
Task	Routine Task/ Non-Routine Task		Manual Task/ Cognitive Task		Substantially or Fully substituted by AI			
	Routine Task	Non-Routine Task	Manual	Cognitive	Now	Partially in 5-10 years	Fully in 5-10 years	Never
Collection of target data	X		X			X		
Sorting target data	X		X				X	
Checking correctness/ completeness of data	X			X		X		
Provide inputs to enterprise value calculations (e.g. EBITDA)	X			X		X		
Provide inputs to equity price calculations (e.g. adjusted net debt)	X			X		X		
Identify risks and upsides to Target company budget and forecast	X			X		X		
Review balance sheet positions for overvalued/undervalued assets and liabilities, identify off-balance sheet liabilities that may need to be considered in the valuation	X			X			X	
Provide inputs to the sales and purchase agreement (SPA) on additional representations and warranties	X			X				X
Assess historical sales and profitability trends to understand key business drivers, significant one-off items, understand any implications to company performance going forward	X			X		X		
Assess scaleability of the cost base, identify any areas where future performance improvements can be achieved	X			X		X		
Estimate potential synergies post-transaction	X			X				X
Assess historical net working capital trends, identify any key collection risks, identify potential improvement opportunities	X			X		X		
Assess any inherent restrictions to company's cash flow conversion rates	X			X		X		
assess historical and planned capex levels / confirm that they support the planned forecast sales / production growth levels	X			X		X		
Understand the key accounting policies of the company, comment on main judgemental areas, deviations from usual industry practices	X			X			X	
15 tasks in total	15 (100 %)	0 (0 %)	2 (13 %)	13 (87 %)	0 (0 %)	10 (66 %)	3 (20 %)	2 (13 %)

Appendix 8 - Advanced Task Model Frameworks – Commercial Due Diligence

CDD								
Task	Routine Task/ Non-Routine Task		Manual Task/ Cognitive Task		Substantially or Fully substituted by AI			
	Routine Task	Non-Routine Task	Manual	Cognitive	Now	Partially in 5-10 years	Fully in 5-10 years	Never
Collection of target data	Y		Y		Y		Y	
Sorting target data		Y	Y		Y		Y	
Execution of External Interviews with customers or experts	Y		Y			Y		
Execution of Internal Target Interviews	Y		Y			Y		
Evaluation of interviews		Y	Y			Y		
Extraction of Data from News, Market Analyses, Public financial data	Y			Y	Y		Y	
Checking correctness of data	Y		Y			Y		
Analysing of market studies, business plans, strategy paper		Y		Y		Y		
Analysing Market growth	Y			Y			Y	
Analysing Market Commercial Trends		Y		Y		Y		
Analysing major market trends	Y			Y		Y		
Analysing Market size	Y			Y		Y		
Identification of Entry Barriers	Y		Y			Y		
Identification of Key Competitors	Y		Y		Y		Y	
Analysing Customer Needs	Y			Y		Y		
Analysing Demand Drivers	Y			Y		Y		
Target pricing analysis	Y		Y				Y	
Analysing growth driver		Y	Y			Y		
Target Analyses of sales, costs & financing	Y			Y	Y		Y	
19 tasks in total	14 (74 %)	5 (26 %)	10 (53 %)	9 (47 %)	5 (26 %)	12 (63%)	7 (37 %)	0 (0 %)