Politecnico di Torino

Master's Degree Course in Management and Engineering
a.y. 2023/2024

October 2024 Graduation Session

Will M&A activities continue to be labour intensive?

An analysis of the potential of technology and data-driven M&A

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Abstract

It is now evident that technology will have a significant impact across all sectors, and the M&A environment is no exception. This is illustrated by the technologies currently in use, the substantial investments made and projected, and the rapid rate of technological advancement. However, due to the growing importance of technology in providing a competitive advantage, and given its position at the technological frontier, a comprehensive overview of the application of advanced technologies across the various phases of the M&A process remains lacking in the literature. Research in this area appears fragmented, often presenting conflicting views due to its exploratory nature and the inherent complexity of M&A processes. This master thesis aims to provide a unified overview of the potential for AI, Blockchain, and Big Data integration in M&A, synthesizing the most influential findings through bibliometric and content analysis, while suggesting possible directions for future research and practical applications.

Keywords: Mergers and Acquisitions; Artificial Intelligence; Blockchain; Big Data; Bibliometric analysis.

Contents

List of Figures

List of Tables

Introduction

Study Rationale

Mergers and Acquisitions (M&A) represent one of the most impactful activities in the life of a company, both in terms of the commitment and resources required, as well as the potential effects. The reasons behind M&A transactions are varied, but they are deeply rooted in the life cycle of companies (both private and public) to the extent that virtually no major company or industry across the globe remains unaffected by M&A activity (D. P. Stowell and P. Stowell, 2024). However, alongside their significance, it is equally important to acknowledge their inherent complexity.

M&A is a multi-level, multidisciplinary, and multi-stage phenomenon that demands specialized expertise and knowledge (Angwin, 2007a), often involving the execution of intricate and time-consuming tasks under tight deadlines (Javidan et al., 2004). Due to these complexities, a vast body of literature has emerged over time (Gomes et al., 2013), seeking to understand the intricacies of M&A. Despite these efforts, M&A transactions remain partially understood ex-ante, as they often represent idiosyncratic and unique transactions (Zagelmeyer et al., 2018). Over time, a traditional approach has been developed, and various technologies have been introduced into the process to enhance its effectiveness and efficiency (Kenneth H. Marks and Stewart, 2022). Nevertheless, the complexity of the required actions and the uniqueness of each transaction have historically limited the impact of technology, leaving M&A processes largely labor-intensive.

With the advent of more dynamic technologies and the increase in computational power, the role of technology in M&A could undergo a significant transformation, shifting from a supportive tool to a game-changing component capable of revolutionizing the traditional approach (Noghrehkar, 2023).

In today's digitalized world, every phase of the M&A process involves the use of technology, including in "technology" also basic tools such as spreadsheets or collaborative work platforms. However, only a few phases integrate cutting-edge concepts like artificial intelligence, blockchain, and big data. While numerous consultancy reports highlight the potential for these technologies to revolutionize M&A (Siegal and Houston, 2024; Ungerman, 2017; Tobias Kohler and Conreder, 2020;

Vogelsang, 2024; Ben Ellencweig and Julia Berbel, 2024; Adam Reilly and Winer, 2024), the academic literature remains fragmented, with research strands that often fail to communicate effectively with one another.

The absence of a mature body of literature and the scarcity of available data for research may be attributed to the significance such data holds for companies today, particularly for those providing M&A services like consulting firms and investment banks (Joy, 2018). Even the most up-to-date and comprehensive databases do not track how these technologies are employed across different M&A phases or their impact on transaction performance. Moreover, direct inquiries to firms often yield little information, as they are unwilling to share data that constitutes a key competitive advantage at this stage.

This gap became evident during the search for data to analyze the relationship between advanced technologies and M&A transaction performance. The difficulty in obtaining such data led to note the absence in the literature of a unifying vision, one that bridges the existing research strands and addresses the opportunities and limitations of integrating technological approaches across the various phases of the M&A process.

This thesis aims to address the current gap by exploring and synthesizing existing research on the application of advanced technologies in the M&A process and identifying areas with limited research that hold potential for future investigation. In doing so, the study proposes a foundation and new directions for subsequent research. To achieve this objective, a bibliometric-content analysis was conducted to assess publication productivity and key aspects of the field, thereby evaluating the current state of research and identifying the most studied applications of advanced technologies in M&A. To determine the white gaps and potential avenues for future research, an exploratory analysis was carried out, integrating the most critical challenges of the M&A process with the strengths of advanced technologies, while incorporating expert and industry perspectives to identify potential applications worthy of further examination. Thus, the thesis has four main objectives, which can be summarized in four questions:

What is the publication productivity? The number and trends of publications in the field of the use of AI, Blockchain, or Big Data in M&A transactions serve as a measure of the growing interest in these topics and, consequently, their impact potential.

Which are the most influential articles? Since this work aims to provide a foundation for future research, identifying the key and seminal articles in the field is crucial to facilitate future studies.

What are the most typical themes? The content within the body of knowledge indicates where research has been concentrated so far (in which phases of the process, with which technologies), thus outlining the current state of the field.

What are the promising areas? Topics that have not yet been widely researched but appear promising represent potential directions for future research.

Prior literature reviews

Given the broad scope and inherent complexity of the M&A process, several studies have attempted to explore and organize the research field, resulting in the availability of various literature reviews. Most of these reviews highlight how research in the M&A sector is fragmented, controversial, lacking a dominant framework, and subject to the "silo" effect, with a noticeable absence of a multidisciplinary approach (Eulerich, Kopp, and Fligge, 2022; Gomes et al., 2013; Junni and Teerikangas, 2019; Meglio and Risberg, 2010; Teerikangas, Joseph, and Faulkner, 2012). However, most of the research focuses on the M&A performance drivers (examples are Barkema and Schijven, 2008, Kapoor and Lim, 2007, Zollo and Singh, 2004, and Croci and Petmezas, 2009), and did not touch the digitalization of the process itself. These characteristics become even more pronounced when focusing on the body of work related to the use of advanced technologies in the transaction process, to the point where identifying comprehensive literature reviews on the subject proves challenging. Bedekar et al., 2024, propose an AI-driven framework, but it remains limited and tailored to only the due diligence phase of the process. Hasan, 2022, provides a broad overview of AI applications which, although primarily studied in the context of accounting and auditing, shares intersections with certain M&A procedures, especially due diligence. The structured approach, extensive referenced literature, and the study of AI technology applications by the Big 4 make its conclusions relevant to this study as well.

In the M&A field, significant contributions, not always covered in empirical and theoretical articles, can be found in books. Particularly, the second edition of the "Middle Market Review" (K. Marks et al., 2022a), one of the most recognized handbooks for professionals, presents in Chapter 10 one of the most complete and detailed collections, offering an M&A Technology Framework (Figure 1).

The authors identify seven broad "categories" (six, plus a seventh for comprehensive software) where the application of technology provides the most significant contributions and adds the greatest value. However, this collection is not focused on advanced technologies, including some tools that are now well-integrated into the traditional process. Nonetheless, in the penultimate section, the authors provide a general overview of the use of AI in M&A, suggesting the most likely trends. The authors note the lack of data on this topic, drawing their conclusions from surveys of 37 end users and 15 technology providers. However, the high level of excitement surrounding these topics makes interviews a potentially biased method.

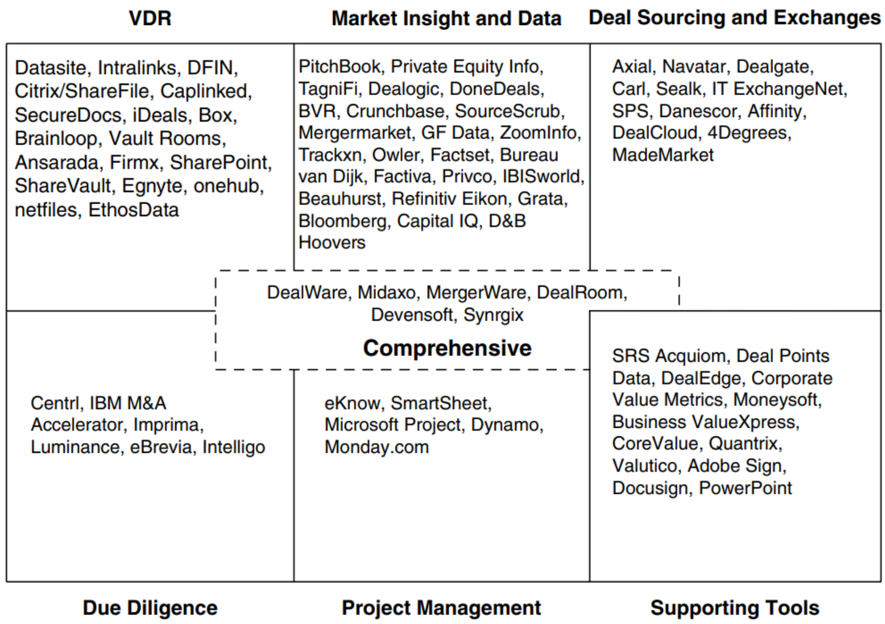


Figure 1: The M&A Technology Framework; a sampling of the available software or technologies for the M&A transactions (K. Marks et al., 2022b).

Therefore, a more data-driven, objective study focused on the use of advanced technology in M&A transactions could offer a valuable contribution to the literature.

Thesis structure and methods

The work is structured as an exploratory analysis aimed at showcasing the potential that advanced technologies such as artificial intelligence, big data, and blockchain may play in the future of M&A processes. The first step is to precisely define the perimeter of the study, outlining the phases and characteristics of the M&A process, as well as the types and features of technologies considered. This is the objective of the **first section**, reached through a qualitative literature review. This comprehensive review is instrumental in establishing the theoretical foundations for the study and is organized around two main themes:

M&A process: ensuring a strong understanding of all phases in typical M&A transactions, detailing the activities performed, the actors involved, critical points, and the systems utilized.

Technologies: providing sufficient knowledge of the main characteristics, functions, and potential of artificial intelligence, blockchain, and big data. In line with the focus of the thesis, technical details are simplified to focus on essential concepts. The aim is not to offer a technical implementation timeline, but rather to identify opportunities for application.

Having established the context, the **second section** presents the results of the bibliometric analysis, addressing the first three questions that underpin this master's thesis and defining the current state of research, as well as identifying the areas in which the application of advanced technologies in M&A has been currently evaluated. The method used is well-established (Pritchard, 1969) and supported by several trusted guidelines for its proper and scientific execution (Donthu et al., 2021; Weng Marc Lim and Ali, 2022; Paul et al., 2021), making it the most suitable approach given the broad scope of the review and the sufficiently large dataset. Unlike other methods, such as meta-analysis or systematic review, content-bibliometric analysis allows for the application of quantitative methods to the literature review, ensuring the objectivity of the results despite a large and heterogeneous dataset of articles. Specifically, the guidelines of the SPAR-4-SLR protocol are followed (Paul et al., 2021), adhering to the four-step procedure presented by Donthu et al., 2021, and taking as an example the application by S. Kumar et al., 2022. In detail, the four steps recommended are:

1. Defining the aims and scope for study: the study aims to explore the bibliometric and intellectual structure of the literature regarding the implementation of AI, Blockchain, and Big Data in the M&A process, using this knowledge to highlight best use-cases and direction to further explore; hence the scope is large being those technologies heavily researched and the M&A process complex and vast.

2. Choosing the techniques for analysis: bibliometric and content analysis will be used, evaluating publication productivity, citation network, keywords co-occurrence, bibliographic coupling, and content analysis.

3. Collecting the data for analysis: see chapter 2.

4. Conducting the analysis and reporting the findings: see chapter 2.

For graphical outputs, VOSviewer (Eck and Waltman, 2010), and Python 3.12 are used. Other software options exist (e.g., Bibliometrix R, Bibexcel, Pajek, SciMat), however, VOSviewer is chosen because it allows for sufficiently complex analyses to meet the scope of the thesis, and is user-friendly. Python, on the other hand, is utilized to create word clouds (providing a visual reference for the results of the bibliographic research) and to conduct a sentiment analysis on the abstracts of the selected articles, aimed at assessing the initial attitude of the research toward this topic. The developed codes used for the analyses are provided in Appendix B.

The BERT (Bidirectional Encoder Representations from Transformers) model, a pre-trained model developed by Google (Devlin et al., 2018), is employed to perform the sentiment analysis, as it is suitable for natural language processing tasks. Due to its bidirectional structure, the model only indicates whether the sentiment is positive or negative, without using a scale, but it also provides a confidence score for each result. The chosen Python development environment was Spyder, executed via Anaconda. The loaded libraries were Pandas (for managing the CSV files extracted from Scopus and manipulating the data), Transformers (for implementing BERT), Torch (a deep learning library supporting Transformers), and Seaborn and Matplotlib (for visualizations).

The **third section** provides a comparison between the needs of the M&A process and the strengths and weaknesses of these technologies, identifying areas for improvement in the traditional process currently not explored in the literature. From this, the study derives 'white gaps' (areas where data is scarce) thereby highlighting the limitations and outlining potential avenues for future research. To bridge academic research with real-world experience, consulting firm reports are consulted in this section and interviews, and discussions were conducted throughout the drafting of the thesis with M&A experts, including partners, senior managers, and managers from leading consulting firms.

An overview of how the work for this master's thesis was organized is presented in Figure 2.

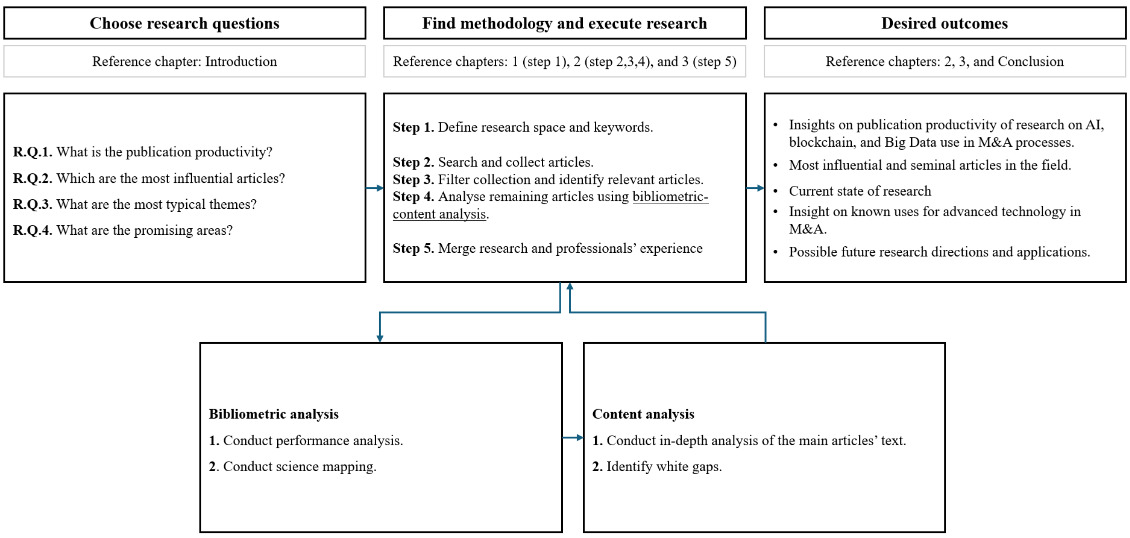


Figure 2: Research design and scheme of analysis, inspired from S. Kumar et al., 2022.

Chapter 1

Contextualization and preliminary definitions

Both the term M&A and the terms artificial intelligence, blockchain, and big data are often broad umbrella concepts with unclear boundaries that, depending on the context, take on different meanings. A precise definition of these terms is essential for the clarity of the study and to establish the scope of analysis.

1.1 Mergers and acquisitions (M&A)

Although the terms merger and acquisition are often used interchangeably and sometimes even considered synonymous with takeover, in practice, they define distinct concepts with different characteristics and implications. Despite the various definitions that have emerged over time, this study adopts the definitions provided in the book "The Art of M&A" (Lajoux, 2024), recognized as the authoritative guide M&A professionals have relied on for 35 years. Specifically, the following definitions are considered:

Merger: when one corporation is combined with and disappears into another corporation. It is a narrow, technical term for a particular legal procedure that may or may not follow an acquisition.

Acquisition: the process by which the stock or assets of a corporation come to be owned by a buyer. It is the generic term used to describe a transfer of ownership. For the purpose of this study, we count as acquisition only transactions where the acquirer purchases the majority of the shares (over 50%) of another company (the "target") or parts of it (for example a business unit or a division).

Takeover: also called hostile acquisition, it is one in which the would-be buyer bypasses the board and management and directs its overtures directly to the target's shareholders. It typically involves publicly traded companies and is generally less common, as most acquisitions are friendly and often initiated by the target company itself.

Overall, the term M&A refers to a series of actions that companies undertake to maintain high levels of competitiveness, support growth (both inorganic and organic), and drive transformational change (M. L. Marks and Mirvis, 2015), typically by capitalizing on the synergies generated between the two (or more) entities involved (Feldman and Hernandez, 2021).

In evaluating the opportunities for implementing advanced technologies, it is crucial not only to understand the M&A process but also the motivations driving companies to engage in M&A activity and the metrics used to assess its success (or failure). After all, technology serves as a tool to be utilized at specific stages of the process, where it is expected to add value and offer improvements over traditional methods, by simplifying, accelerating, or enhancing particular outcomes, ultimately increasing the likelihood and/or level of success. Therefore, to evaluate the use of advanced technologies, it is essential to consider these three perspectives, applying a multi-perspective approach (Meglio and Risberg, 2010). Moreover, implementing technologies such as AI and blockchain represents significant investments, adding a fourth dimension: the presence of a genuine need that justifies their adoption.

1.1.1 The M&A motives

The reasons driving companies to engage in M&A activities are varied and have evolved over time. Exploring why certain behaviors, such as waves of mergers and acquisitions, occur remains one of the puzzles of corporate finance (Yang, 2008). Many studies have examined M&A motives (see Amit, Livnat, and Zarowin, 1989; Nguyen, Yung, and Sun, 2012), yet the research remains highly heterogeneous and difficult to compare, leaving the field without a unified perspective. A key text on M&A motives is "Mergers, Acquisitions, and Corporate Restructurings" (Gaughan, 2017), which provides a comprehensive overview of the financial and strategic rationales behind corporate takeovers. Another seminal contribution comes from Jensen and Meckling, 1976, who explain managerial incentives such as agency costs and their role in influencing M&A decisions. Further studies delve into behavioral aspects, highlighting factors like managerial overconfidence and empire-building as key drivers of acquisition decisions (for example Gervais, 2010; Croci and Petmezas, 2009).

Despite this variability, it is possible to identify several key motives that have remained consistent over time. First, the pursuit of synergies, whether operational or financial, continues to be one of the most enduring drivers of M&A (Feldman and Hernandez, 2021). Companies often seek mergers or acquisitions to reduce costs, improve operational efficiencies, and achieve economies of scale. Similarly, the drive to increase market power through the acquisition of competitors, with the aim of consolidating market share, is a well-documented and stable motive (Gaughan, 2017). This is reinforced by earlier economic theories (Coase, 1937), which explain firms' tendencies to grow in order to reduce transaction costs. Furthermore, firms have used M&A to enhance efficiency, reduce operational redundancies, and compete more effectively in crowded markets. The desire to eliminate competition or solidify market dominance remains a constant across industries and geographies. Diversification is another enduring motive, as firms seek to reduce their exposure to specific market risks by acquiring businesses in unrelated industries (Jensen, 1986).

While some motives have remained stable, others have shifted in response to technological, social, and regulatory changes. One significant shift is the increasing role of technological innovation in M&A activity. In the past, financial synergies and operational efficiencies were the primary motives; today, companies are increasingly acquiring other firms to gain access to technology, innovation, data assets, and R&D (Dang, 2024; Shleifer and Vishny, 2003; Phillips and Zhdanov, 2013). Another relatively new motive is the focus on environmental, social, and governance (ESG) factors. With growing regulatory and societal pressure for sustainability, companies are now incorporating ESG alignment into their acquisition strategies. This trend marks a shift from traditional financially-driven motives to more ethically and socially driven considerations (Gaughan, 2017).

1.1.2 The M&A process

The process for mergers and acquisitions transactions is generally well-documented in academic literature (Cumming et al., 2023; Aggarwal-Gupta, R. Kumar, and Rajesh, 2012), books (Frankel and Forman, 2017; Lajoux, 2024; Emott, 2012), and industry research, with broad consensus on the main phases. While there are variations in the number of steps or their labeling, the high-level structure is widely accepted, typically identifying three main phases: Strategy, Transaction, and Integration, sometimes also described as Precombination, Combination, and Postcombination (M. L. Marks and Mirvis, 2015). The challenges and importance of each step are also extensively studied in the literature, with core (most critical) elements remaining consistent across modern M&A processes: strategy development, due diligence, negotiation, and integration, among others.

Trying to develop a holistic view across all typical phases, the study adopts a seven-step framework resulting from the synthesis of the five-stage approach proposed by Sudarsanam, 2010, the twelve-stage of Lajoux, 2024 (a detailed list of the stages can be found in Appendix A), and the eight-stage of Parvinen and Tikkanen, 2007.

1. **Deal strategy and planning:** the first phase involves defining the strategic rationale for the transaction, and the desired goal before searching for it. The

board of directors, senior management, and M&A advisors (often investment bankers or consultants) are the primary actors, evaluating potential markets, technologies, or capabilities they wish to acquire. Common information in this phase is market analysis, financial reports, competitor data, and internal strategic goals, which are reviewed to form a solid case for the transaction.

A major challenge in this phase is ensuring strategic alignment between the motives of the transaction and the following steps. Poorly defined motives can lead to failed integrations (Angwin, 2007b), and strategic misalignment, such as pursuing acquisitions without clear synergy potential, often results in overpayment or underperformance (Bower, 2001).

2. **Target identification and screening:** defined the scope, potential acquisition targets are identified and screened based on predefined criteria such as financial performance, market position, or technological assets, to evaluate if they respond to the needs. M&A teams, financial analysts, and legal experts collaborate to narrow down potential targets looking at financial statements, market share data, intellectual property, and growth projections are the primary datasets.

   Ensuring an accurate valuation is the most problematic theme. Research (Welch et al., 2020; Parvinen and Tikkanen, 2007) highlights that inaccurate screening and failure to identify hidden liabilities (for example pending lawsuits), technological obsolescence, or evaluating IP assets can lead to overpaying. The challenges in evaluating targets stem not only from asymmetric information but also from the difficulty in information interpretation.

3. **Valuation and due diligence:** this stage involves conducting a detailed assessment of the target's financial health, legal standing, and operational efficiency. Financial modeling techniques are employed to determine a fair purchase price. Data rooms collect detailed financial reports, legal documentation, patents, intellectual property rights, and workforce assessments to let financial advisors, accountants, legal teams, and M&A specialists assess the target.

   This phase is one of the most critical due to the vast amount of data available and the limited time frame (Lajoux, 2024). Inadequate due diligence and missed risk factors and red flags are some of the primary causes of failed M&A deals (Bedekar et al., 2024); a successful due diligence process requires a strong multidisciplinary approach, which is often lacking due to the financial focus driven by the backgrounds of those typically involved in the process.

4. **Negotiation and deal structuring:** once due diligence is completed, Legal advisors, investment bankers, and senior management from both firms engage in negotiations to finalize the terms of the deal, including pricing, payment structure, and any contingent agreements.

   One of the most debated aspects is structuring the payment (cash, stock, or a mix), as research highlights that misalignment in expectations here can derail deals (Eckbo, 2009). Negotiation power dynamics and cultural differences are also important factors to consider.

5. **Regulatory approval:** the deal must be approved by relevant regulatory bodies, especially in industries with high governmental oversight (e.g., telecom, banking). Regulatory filings, compliance documents, and market impact studies are submitted by legal teams and government agencies, and antitrust bodies evaluate the deal.

   Here, one critical issue is the increasing complexity of regulatory requirements, particularly in cross-border deals, and the formal requirement of the submitted documents. Approval can be delayed or denied, especially if regulators believe the deal reduces competition (Lajoux, 2024), and delays can derail transactions.

6. **Integration planning and execution:** this phase involves combining the processes, cultures, and technologies of both companies, generating a unified entity that can leverage the initially planned synergies and, as a result, achieve a value greater than the sum of the individual companies. Process maps, technology infrastructure plan, workforce assessments, and communication strategies are common tools used.

   Integration is often cited as the most challenging part of the M&A process, even more than the due diligence phase, and the one most influencing the returns of the operation. Research extensively explores the dynamics of integration, but it remains an extremely complex process, heavily influenced by a wide range of internal and external variables. Failure to integrate technology systems, misalignment in corporate cultures, and talent retention issues are common causes of post-merger failures (King et al., 2004).

7. **Post-Merger Performance Review:** After the merger, the performance of the combined entity is evaluated against the deal's original objectives. The goal is not only to assess the work done but also to continuously monitor the evolution of the new entity and to identify corrective and improvement measures as early as possible. Performance metrics, financial reports, employee satisfaction surveys, and customer feedback are typically used by teams to monitor outcomes.

   One critical issue is that post-merger performance reviews are often neglected or under-prioritized. Regularly monitoring performance and adjusting strategies is crucial. Moreover, along with Stage 6, this phase involves implementing the most significant changes for the acquired or merged company, making the communication strategy employed by management (Zagelmeyer et al., 2018) and the emotions conveyed (Klok, Kroon, and Khapova, 2023) essential to fostering a change-friendly environment that aligns with the buyer. Research has long recognized the importance of human factors (Pucik and Evans, 2004).

1.1.3 The M&A measures of success

The literature is unclear regarding the metrics used to evaluate the success of M&A activities. These transactions encompass so many aspects of corporate life that there are numerous perspectives to consider, making it difficult to rely on a single measure. Defining success from the perspective of financial markets, a transaction is considered successful when the combined entity's value exceeds the sum of the pre-transaction values of the separate entities (Canina, J.-Y. Kim, and Ma, 2010). From this perspective, researchers have typically measured success using financial metrics, most commonly through positive abnormal returns at the time of the announcement. While this metric has been used for a long time (Jensen and Ruback, 1983), it has the limitation of assuming efficient markets, which is not always the case, as performance can be biased by managerial optimism or pessimism (Canina, J.-Y. Kim, and Ma, 2010). Similarly, long-run performance, focusing on cumulative abnormal returns (CAR), is not very relevant as it is an ex-post measure and thus does not support decision-making.

Given the limitations of financial measures — despite their effectiveness in synthesizing the diverse variables in M&A (culture, systems, employees, morale, etc.) — researchers continue to use CAR as the primary measure of success. However, they now seek to correlate CAR with ex-ante factors that can be evaluated during the transaction, in order to predict the success or failure of a deal. These factors, referred to as success factors, serve as indicators of potential high CAR.

Building on the work of Gomes et al., 2013, and expanding the findings with other research, the main success factors are divided into three categories.

Strategy critical success factors:

- Strategic and organizational fit between the companies involved;
- Stock over cash for payment and reduced overprice (Moeller, Schlingemann, and Stulz, 2005);
- Similar size and organization between the companies involved;
- Precise goals and past M&A experience (Aktas, Bodt, and Roll, 2013).

Transaction critical success factors:

- Presence of a courtship period to let the companies collaborate and get to know each other;
- Fair, accurate, reflexive communication with clear expectations;
- Carefully designed compensation schemes to ensure the involvement of managers but reduced opportunistic behavior;

Integration critical success factors:

- Ensure the right integration, building on complementary scientific and technological knowledge to take advantage of synergies while ensuring autonomy and knowledge sharing of the acquired company;
- Strong leadership establishing clear company direction and managing the necessary change (which should be clearly identified);
- Quick-enough integration, building on momentum with consistency but without creating excessive conflict;
- Dedicated team, so that top management doesn't lose focus from day-to-day activities;
- Control on communication and emotions, reducing uncertainty and insecurity of stakeholders while avoiding overcommunication;
- Analyse cultural differences;
- High HR processes quality, training employees to deal with conflict and new assignments during the integration period, reducing fear and uncertainty.

Once the success factors have been defined, any application of advanced technologies that has the potential to enhance one of these factors also has the potential to add value and, therefore, represents a viable use case (considering the costs).

1.1.4 The M&A activity

Despite still lagging behind pre-COVID levels and the rise in interest rates (in 2021, global M&A activity reached $5.236 trillion with 58.308 transactions, averaging $90 million per transaction), the M&A market remains substantial, with an expected value of $2.546 trillion in 2024 (Figure 1.1).

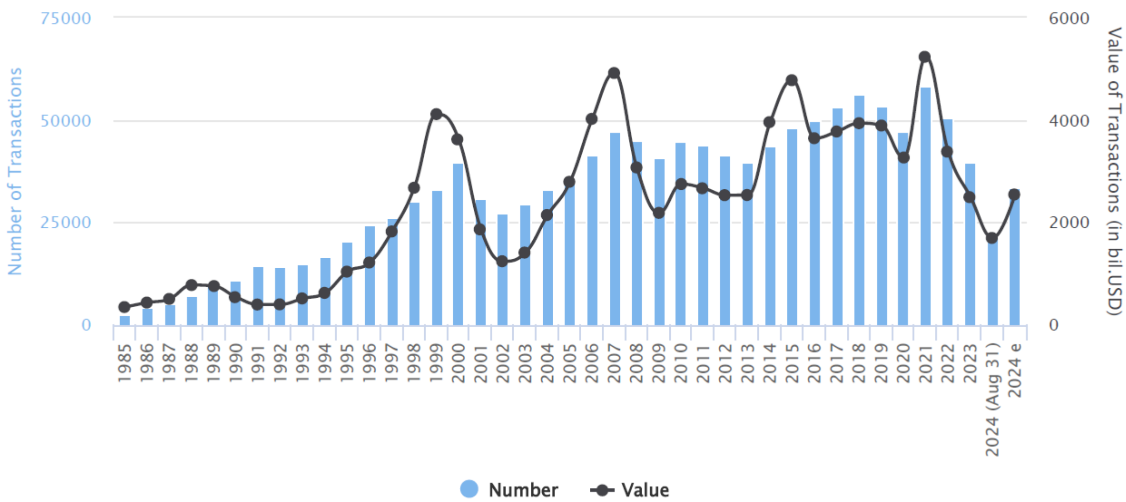


Figure 1.1: Number and value of M&A Worldwide (IMAA analysis, sep. 2024).

On average, the entire process from initial contact to closure (excluding integration, which can take years) lasts between 120 and 240 days. During this short time, the volume of activities, data to be reviewed, and documents to be produced make the process extremely time-critical. As previously highlighted, delays can lead to increased costs, loss of competitive advantage, and even deal termination. Given the sensitivity of each phase and the value of these transactions, substantial investments in advanced technologies are made to mitigate the risks of failure (ICAEW and Drooms, 2019). This, coupled with the increasing focus of research on this topic, underscores the current and significant relevance of integrating advanced technologies into the process. Technology has the potential to reduce time, increase accuracy, lower costs, and minimize manual work. This justifies the present study and highlights the interest in innovation in the sector, especially in anticipation of the upcoming wave.

1.2 Advanced technology

Advanced technologies are defined as "technologies that are still immature but promise to deliver significant value, or that have some technical maturity but still have relatively few users" (Gartner, 2024a).

Digital technologies, on the other hand, are defined as those that use the representation of physical items or activities through binary code to enhance organizational processes, improve interactions between people, organizations, and things, or enable new business models (Gartner, 2024b).

The technologies considered in this study represent the most promising and well-known at the intersection of digital and advanced technologies. However, this set remains broad, and it would not be feasible to analyze all elements comprehensively. To identify the key technologies on which to focus, a co-occurrence analysis was conducted using the VOSviewer tool, drawing from 8,293 articles related to the use of technology in business contexts. Based on the results, the most frequently cited topics in discussions of advanced and digital technology were identified (Figure 1.2). By intersecting these results, the following macro-themes emerged:

- Artificial Intelligence (AI): the most relevant topic.
- Machine Learning: considered and included within the broader category of AI.
- Big Data: the second most relevant topic.
- Blockchain: a less explored topic but one that is strongly correlated with other relevant areas.
- Cloud Computing: excluded due to its low occurrence in the dataset.
- Internet of Things (IoT): excluded, as although widely studied in business applications, it has limited applicability to the M&A sector.

- Other keywords such as "Human", "Industry 4.0", and "Sustainability" were excluded as they do not pertain to a single, specific technology.

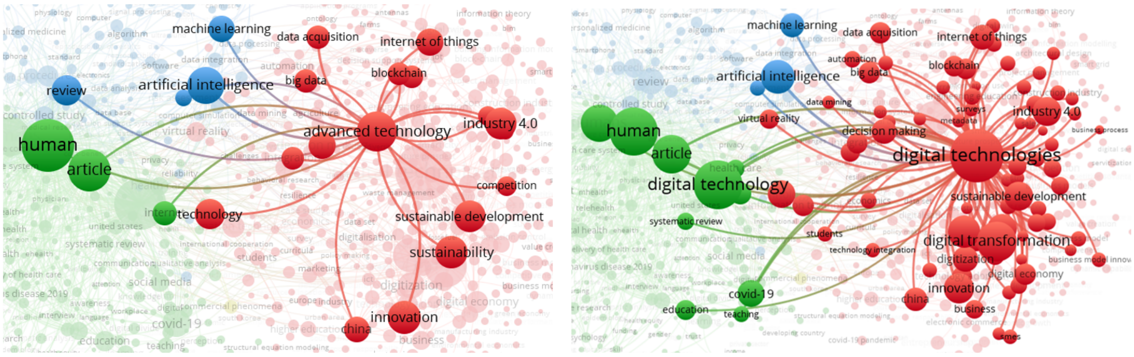


Figure 1.2: Topic co-occurrence in articles regarding advanced technology (left) and digital technology (right).

1.2.1 Artificial intelligence

Considering artificial intelligence (AI) in its broader sense, it is defined as “a technical and scientific field dedicated to the development of engineered systems that generate outputs such as content, predictions, recommendations, or decisions for a given set of human-defined objectives” (ITTF, 2022). Therefore, AI is not a specific tool, but a broad category encompassing various tools designed to produce specific outputs based on human goals. However, in common usage, AI often refers to machines capable of learning, reasoning, and problem-solving (S. Kumar et al., 2022). This latter definition, while not incorrect, is imprecise, as it refers to a subset of AI known as Generative AI (Gen AI).

The latest evolution of Generative AI is the Large Language Models (LLMs), which have the additional ability to be applied to general contexts, rather than just specific tasks. The development of LLMs was not sudden but resulted from the evolution of increasingly sophisticated concepts (IBM, 2024). The first major step was the development of Machine Learning (ML), an approach where machines learn from datasets labeled according to human-defined rules, also known as supervised learning. Subsequently, the field moved to Neural Networks, inspired by the biological functioning of the human brain, which enables systems to learn in more complex ways compared to basic supervised learning. This was followed by the advancement of Deep Learning (DL), which allows systems to learn from unlabeled data, autonomously developing the rules used for interpreting the data.

There is a substantial and reliable body of literature that explores which tasks are best suited to different technologies, as well as their main limitations (Shiri et al., 2023; Alzubaidi et al., 2021; Taye, 2023). The study refers to all these AI subcategories, as different technologies have distinct applications and could bring specific advantages to the M&A process. Table 1.1 provides an overview of where these technologies excel and highlights the key drawbacks to consider when assessing their application.

Table 1.1: Summary of best-suited tasks and drawbacks for AI technologies

Technology	Best suited tasks	Drawbacks
AI	• Complex decision-making tasks • Pattern recognition • Prediction • Optimization • Learning and adapting • Dynamic environments requiring real-time decision-making	• Lack of interpretability • Lack of transparency • Low trust and deployment in sensitive fields • Perpetuate biases present in training data
Machine learning	• Classification • Clustering • Regression • Patterns detection • Predictions from structured data • Optimization tasks	• Highly data-dependent • Require extensive preprocessing • Prone to overfitting on small or noisy datasets • Domain-specific
Neural networks	• Hierarchical pattern recognition identifying intricate, non-linear relationships • Multiple layers of abstraction • Anomaly detection • Predictive modeling	• Overfitting, especially with small datasets • Black-box nature and difficult to interpret • Low deployment in tasks requiring clear decision rationales • Gradient vanishing and exploding issues
Deep learning	• Processing vast amounts of unstructured data (images, audio, and text) • Complex feature extraction • High-dimensional data analysis learning without human intervention	• Computationally expensive • Require vast amounts of data to train effectively • difficult to interpret • Low deployment in tasks requiring transparency and accountability
Large Language Models	• Natural language understanding • Language modeling • Identify relationships between words (text interpretation) • Produce coherent texts (sentence generation)	• Vast computational resources and data • High training costs • Generate factually incorrect or biased information • Low deployment in high-stakes decision-making • Hallucinate when they lack sufficient knowledge

Since the term AI encompasses the broadest category, in this study, all the mentioned technologies will be referred to when discussing AI.

1.2.2 Blockchain

Since its introduction with cryptocurrencies (Nakamoto, 2009), blockchain has been a hot topic recognized for its potential to transform traditional processes through its features of traceability, decentralization, and immutability. Blockchain is defined as "a distributed digital ledger of cryptographically-signed transactions that are grouped into blocks" (Yaga et al., 2018); in simpler terms, it is a transaction and data management technology, and the simplicity of its basic function (securely storing and exchanging transactions) allows for a wide range of applications (Sunny et al., 2022).

Blockchains can be differentiated based on type or underlying technology. For the purposes of this study, the differentiation by type (private, public, consortium) is not particularly critical; it is sufficient to know that they are differentiated in terms of who has the rights to read or add transactions, with implications for scalability, performance, and privacy (Aithal et al., 2021). More relevant is the distinction based on technology (Tripathi, Ahad, and Casalino, 2023), which aids in understanding the strengths and limitations of blockchain usage, and thus assists in the subsequent application of this technology to the M&A process. Additionally, some studies refer to these technologies without specifically mentioning blockchain, so it is important to be aware of the terms used to conduct a thorough bibliometric analysis.

Smart Contracts: mainly used in public blockchains for the automation and programmability of contracts.

Consensus Mechanisms: pillars to all types of blockchains, ensure that all participants in the network agree on the state of the blockchain.

Cryptographic Hash Functions: pillars to all types of blockchains to secure data and ensure integrity.

Distributed Ledger Technology (DLT): allows for the decentralized recording of transactions across multiple nodes, which enhances transparency and reduces tampering risks in distributed schemes (not necessarily blockchain, but also traditional distributed database).

Zero-Knowledge Proofs (ZKPs): mainly used in privacy-focused blockchains, allow for proving the validity of information without revealing the information itself.

1.2.3 Big data

Big Data is a term that has been widely recognized in the literature (Diebold, 2012) and is commonly used in professional discourse. It refers to an exceptionally large collection of data, characterized by high velocity, variety, and, typically, a lack of structure. It is inherent in its definition that for such a massive amount of data to be useful, appropriate technologies and methods must be in place for its processing and analysis (De Mauro, Greco, and Grimaldi, 2016). In this study, Big Data should be considered in relation to the methods and tools that render such data valuable and actionable, which form the so-called Big Data Analytics. Inevitably, this topic partially overlaps with tools such as machine learning, neural networks, and AI, therefore, the concept of Big Data is restricted to tools capable of handling large datasets (even) without the use of AI or blockchain such as: A/B testing, cluster analysis, data fusion and data integration, ensemble learning, genetic algorithms, regression, sentiment analysis, signal processing, spatial analysis, advanced statistics, and advanced analytics.

Chapter 2

Content-bibliometric analysis

2.1 Collecting the data for analysis

The first step in conducting a bibliometric analysis is data collection, which involves gathering academic articles related to the subject under examination. For this purpose, Scopus was selected as the data source. Scopus is the largest scientific database for peer-reviewed research publications and is widely recognized and used in the literature as a reliable and sufficiently comprehensive source of publications (Donthu et al., 2021; Paul et al., 2021), with social sciences (in which finance is included) being the dominant subject area (29%, Elsevier, 2024).

Through its advanced search functions, Scopus allows the use of logical constructs to optimize searches and precisely specify the type and content of the desired articles. Additionally, with its precise article uploading rules, it enables not only the viewing but also the exportation of data in specific formats (particularly .csv and .ris, essential for subsequent analyses) including citation information, bibliographical information, abstract, keywords, funding details, and other information. Exporting data in .csv format up to 20,000 articles allows for large-scale processing of extensive literature comprehensively and efficiently. Scopus Preview (a free tool) only allows partial searches and provides limited extraction, filtering, and access capabilities. For this study, full access to all functionalities was available thanks to the full license provided by Iowa State University and the Polytechnic of Milan.

Once the source database has been defined, a crucial step for ensuring the quality of the results is the formulation of the search string. Essentially, the desired literature consists of articles that combine two main themes: advanced technology (as identified in section 1) and M&A. These concepts, represented by keywords, must both be present within the desired articles and, therefore, should be connected using a logical AND operator.

To ensure that the concepts are comprehensively captured in the search, the development of keywords was informed by interviews with industry professionals (specifically senior managers and partners with expertise in innovation within the transaction field) and previous research that applied bibliometric approaches (S. Kumar et al., 2022; Cumming et al., 2023; Gomes et al., 2013; Chiaramonte et al., 2023). As a result, the search string is divided into two main sub-strings:

- A first section identifies advanced technologies with typical keywords indicating AI, Blockchain, Big Data, or their relevant applications (such as deep learning, Ethereum, smart contracts). There is no interest in the simultaneous use of these technologies, therefore, all keywords are connected using the logical operator OR.

- A second section identifies the broader M&A theme. Key elements of its process (such as due diligence and integration) were also included, as some papers evaluate the application of advanced technologies to specific stages without mentioning the broader M&A framework, being those stages common to other themes (such as IPO, real estate, ERP change).

  It is important to note that it is challenging to specifically identify the M&A process without including the broader concept of M&A and its applications. However, this step is crucial as we are not interested in transactions concerning advanced technologies, but rather in the use of such technologies in executing the transaction. This identification cannot be effectively achieved using keywords and logical constructs alone, so articles unrelated to the M&A process were filtered out by personally reviewing titles and abstracts.

The search for articles was conducted in September 2024, resulting in a total of 85 selected articles. This is a relatively low number, reflecting the specificity of the topic and the still largely exploratory nature of research in this area. The technologies under investigation are a hot topic of great interest, as evidenced by the size of the initial results. However, their applications in M&A have not yet been extensively identified in the academic literature. The search process followed five steps:

Step 1: search for articles related to advanced technologies using Scopus search string.

Table 2.1: Starting search string and results.

Search string	Results
TITLE-ABS-KEY("Machine Learning" OR "AI" OR "Neural Network" OR "Artificial Intelligence" OR "Deep Learning“ OR "Blockchain" OR "Block-chain" OR "Bitcoin" OR "Ethereum" OR "Hyperledger" OR "Cryptocurrency" OR "Smart contract" OR "Distributed Ledger Technology" OR "DLT" OR "Distributed Ledger“ OR "Big Data" OR "Big-Data" OR "Advanced Analytics")	2,434,506 (100%)

Step 2: search for articles related to advanced technologies specifically in the M&A sector using Scopus search string.

Table 2.2: Search string refinement, results, and percentage retained from step 1.

Search string	Results
(TITLE-ABS-KEY("Machine Learning" OR "AI" OR "Neural Network" OR "Artificial Intelligence" OR "Deep Learning“ OR "Blockchain" OR "Block-chain" OR "Bitcoin" OR "Ethereum" OR "Hyperledger" OR "Cryptocurrency" OR "Smart contract" OR "Distributed Ledger Technology" OR "DLT" OR "Distributed Ledger“ OR "Big Data" OR "Big-Data" OR "Advanced Analytics")) AND (TITLE-ABS-KEY("M&A" OR "Merger* " OR "mergers and acquisitions" OR "merger and acquisition" OR "mergers & acquisitions" OR "consolidation* "))	5,664 (0.23%)

Step 3: filter the search results using Scopus filters by document type (articles or reviews), source type (journal), and language (English).

Table 2.3: Applied filters, results, and percentage retained from step 2.

Filter string	Results
AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j"))	3,024 (53,39%)

Step 4: filter refinement by subject areas (social sciences; business, management and accounting; Multidisciplinary; decision sciences; economics, econometrics and finance).

Table 2.4: Filter refinement, results, and percentage retained from step 3.

Filter string	Results
AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "MULT") OR LIMIT-TO (SUBJAREA , "ECON") OR LIMIT-TO (SUBJAREA , "DECI"))	438 (14,48%)

Step 5: review of titles and abstracts to exclude articles not focused on the application of advanced technologies in the M&A process.

Table 2.5: Manual selection criteria, results, and percentage retained from step 4.

Selection criteria	Results
The title and abstract focus on the use of advanced technologies in the M&A process or give insight into this theme	85 (19,41%)

Out of the 438 articles identified in the final step on Scopus, 353 articles were discarded after review (80.59%). The predominant reason for this exclusion was that the articles pertained to other domains of knowledge (primarily memory sciences, linguistics, and medicine). Additionally, many articles employed advanced technologies in their methods but did not actually discuss their application within the M&A process. Thus, although they mentioned M&A and advanced technologies, they are not relevant to the study.

Of the 353 discarded articles, 29 did not meet the parameters of the bibliometric analysis and were therefore not included, however, they provide interesting and potentially valuable insights. Consequently, they were read in their entirety, just like the 85 selected articles, and were utilized for the discussions in Chapter 3.

2.2 Conducting the analysis and reporting the findings

Having identified the relevant articles and established the foundation for analysis, the final step was to proceed with the actual content-bibliometric analysis.

2.2.1 Pubblication productivity

To analyze publication productivity, the distribution of selected publications over time was examined (see Figure 2.1). As expected, a clear upward trend is observed, consistent with the growing prevalence and reliability of advanced technologies and the increasing demand for innovation in traditional M&A processes. This reflects the fact that this field remains an emerging area of research, attracting increasing interest, although production is still relatively low.

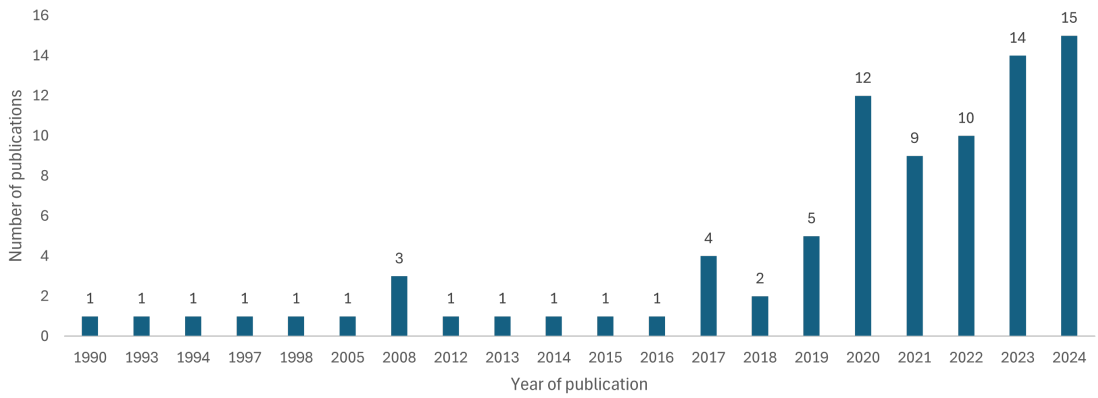


Figure 2.1: Publication productivity in the domain of the application of advanced technology in the M&A process.

The first publication in 1990 was unexpected. The article "MARS: A Mergers and Acquisitions Reasoning System" (Bonissone and Dutta, 1990) already acknowledged the complexity of the M&A process and the relevance of the topic, given the

M&A boom of that year with a record number of transactions in America. The two authors, recognizing the significant role of computers, introduced MARS as an early attempt to apply artificial intelligence to demonstrate its utility in finance. The "reasoning system" was applied horizontally across the process and supported decision-making in uncertain contexts through simulations, natural language interaction, and planning.

2.2.2 Most influential articles

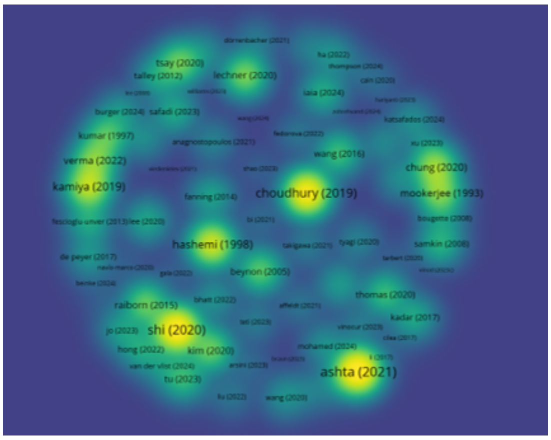
Various metrics exist to measure the influence of a publication. In this thesis, the prevalent view in the literature is followed, using citations by other publications as a measure of an article's influence. Table 2.6 presents the top five most-cited articles, while the Figure 2.2 illustrates the impact of individual publications and the contribution of different countries to the field.

Table 2.6: Most influential articles measured by number of citations.

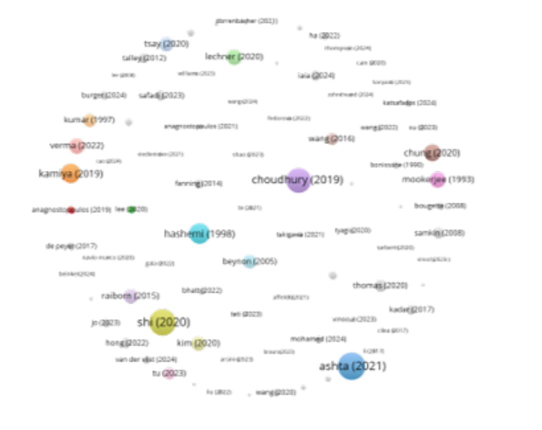
Title	Author(s)	Year	Journal	Citations
Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance	Ashta A.; Herrmann H.	2021	Strategic Change	116
TOward a better measure of business proximity: Topic modeling for industry intelligence	Shi Z.M.; Lee G.M.; Whinston A.B.	2020	MIS Quarterly: Management Information Systems	109
Machine learning approaches to facial and text analysis: Discovering CEO oral communication styles	Choudhury P.; Wang D.; Carlson N.A.; Khanna T.	2019	Strategic Management Journal	95
A hybrid intelligent system for predicting bank holding structures	Hashemi R.R.; Le Blanc L.A.; Rucks C.T.; Rajaratnam A.	1998	European Journal of Operational Research	65
The face of risk: CEO facial masculinity and firm risk	Kamiya S.; Kim Y.H.A.; Park S.	2019	European Financial Management	58

As expected, given the country's historically vibrant M&A activity, the United States dominates the field both in terms of published documents and citations (Figure 2.2-c&d). China, South Korea, and the UK demonstrate strong output (in terms of quantity), yet they remain relatively uninfluential. In contrast, France appears to exert significant influence despite lower productivity. Moreover, as evidenced by the citation network among publications (Figure 2.2-b), studies remain fragmented and disconnected (no edges between publications). This aligns with observations in the literature regarding the lack of a comprehensive framework that facilitates smooth collaboration and the identification of key experts in the field to refer to.

With 116 citations in no more than three years, Ashta and Herrmann, 2021, stands as the most influential article in the field of applying advanced technologies within the M&A process. Through case studies and interviews, the authors provide an overview of the current state of AI in the financial sector, identifying key applications (Risk Management, Customer Targeting, and Customer Engagement) and addressing prevalent concerns among professionals. They also suggest

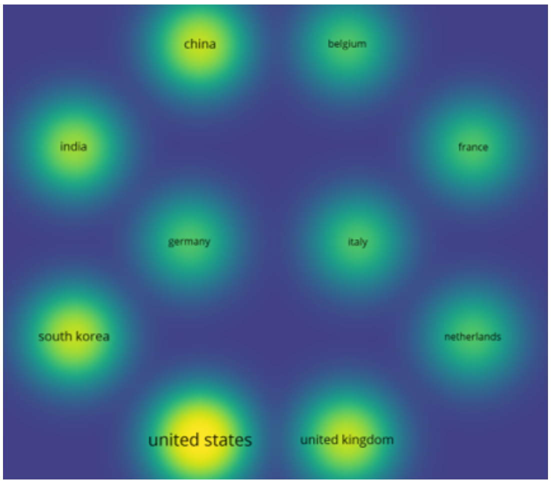


(a) Citation density for articles.



(b) Citation network.

(c) Citation density by country.



(d) Production density by county.

Figure 2.2: Representation of the impact of individual publications (a), researcher collaboration (b), and the impact (c) and productivity (d) of countries.

future research directions in areas such as the maturity of Auto-ML tools, training data, explainability, model management, performance and monitoring, and privacy. Specifically within the M&A context, AI appears to be particularly suited for data analysis phases (primarily in the stages of deal strategy, target identification, valuation, and due diligence). However, concerns persist regarding its applicability to financial data due to the high level of noise that characterizes such data, as well as issues of responsibility in the event of errors.

Shi, G. M. Lee, and Whinston, 2014, develops an application of big data analytics for evaluating business proximity. As indicated in Chapter 1, this factor is one of the key success drivers, making innovative methods for assessing proximity in the spaces of product, market, and technology potentially highly impactful. The article takes a technical approach, ultimately developing an interface for the application of this technology, which is intended for use in the strategy and transaction phases.

Choudhury et al., 2019, similarly to Kamiya, Y. H. Kim, and S. Park, 2019, explore the use of unsupervised topic modeling of text data, sentiment analysis, and supervised ML coding of facial images, together with a convolutional neural network algorithm, to map CEO communication styles. Communication is another critical success factor, and the ability to develop AI capable of replicating a specific communication style can have a significant impact during negotiation and post-merger integration phases.

2.2.3 Most typical topics

As suggested by S. Kumar et al., 2022, the authors' keywords of articles are a good measure of their topical coverage, and, therefore, can be used to assess the topics on which current research is focused. Their co-occurrence, on the other hand, serves as a useful indicator of the prevailing topical trends in the field.

To evaluate the topical coverage and trends in research concerning the application of advanced technologies in the M&A process, the authors' keywords from the 85 selected articles were analyzed using VOSviewer and Python. To ensure consistent results, the data was slightly processed before the analysis to standardize keywords related to the same topic but expressed differently across the articles (e.g., "mergers" for "merger," "AI" for "artificial intelligence," "M&A" for "mergers and acquisitions," etc.). This analysis yielded three main findings.

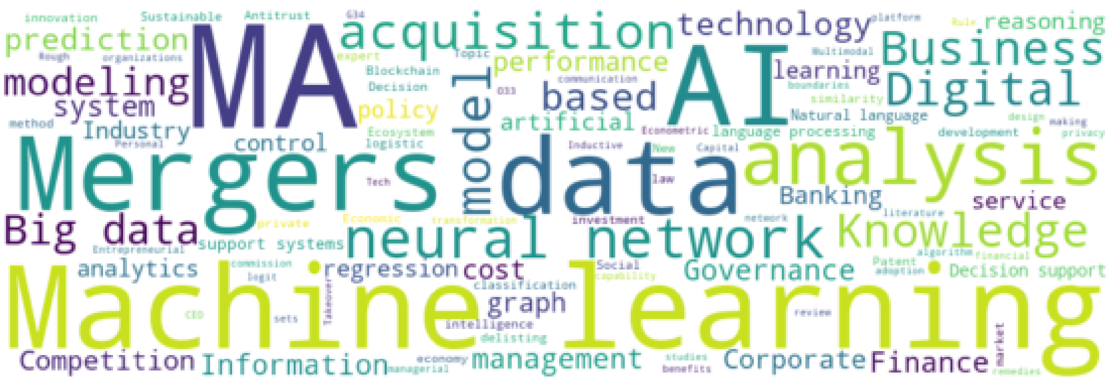


Figure 2.3: Word cloud on author's keywords among the 85 articles selected.

Firstly, as shown in Figure 2.3 and detailed in Table 2.7, left, the most prominent keyword is M&A, with 23 occurrences among the 85 articles analyzed, followed by machine learning (16 occurrences), mergers (11), and AI (10). These findings are consistent with the search criteria used during the collection phase and demonstrate that the most extensively studied technology in the context of the M&A process to date is machine learning. This result is also expected, considering that machine learning is among the most mature branches of AI and, therefore, better suited for application in error-free contexts, such as financial due diligence or valuation.

Table 2.7: Top author's keywords by frequency of occurrence (left) and top keyword pairs by degree of co-occurrence (right).

Keyword	Occurrence
M&A	23
Machine learning	16
Mergers	11
AI	10
Big data	5
Banking	4
Decision support systems	4
Natural language processing	4
Neural networks	4
Prediction	4

Keyword 1	Keyword 2	Weight
M&A	Machine learning	9
Big data	Mergers	4
Control	Mergers	3
M&A	Modeling	3
AI	Banking	2
AI	Decision support systems	2
Antitrust	Mergers	2
Banking	Mergers	2
Big data	Competition	2
Big data	Competition law	2

Secondly, analyzing the keyword pairs based on the relevance of their links (Table 2.7, right), two M&A-technology combinations emerge as the most common in the literature: M&A and machine learning, and mergers and big data. This result confirms that the dataset meets the needs of the investigation, and demonstrates that machine learning is the advanced technology with the most studied applications in M&A to date, alongside big data, particularly in the context of mergers and the regulatory approval phase of the transaction.

Finally, the topic network (Figure 2.4) that emerged from the authors' keywords of the 85 articles confirms the previous findings while offering a broader overview. Here, the size of the nodes represents the frequency of occurrence of the keywords across the various articles, while the thickness of the links measures the strength of the connection in terms of the number of articles in which these topics co-occur. As the analysis reveals, the total of 268 keywords and 1,129 links can be organized into 10 main clusters based on similarity and co-occurrence frequency, which identify the 10 principal macro-topics around which the research has developed:

- The largest cluster (red) includes 61 keywords and pertains to the application of machine learning in the M&A domain, ranging from supporting analyses to policy review and synergy evaluation.
- The second largest cluster (green) encompasses 39 items and is focused on the use of AI in the banking sector.
- The third cluster (blue) groups 29 keywords and concentrates on the use of big data in mergers. In this cluster, the theme of regulatory approval is particularly relevant, as current European regulations have focused heavily on data when evaluating M&A transactions.

- The fourth cluster (yellow) includes 28 items and relates to the use of neural networks and genetic algorithms for decision-making support.
- The fifth cluster (purple) includes 26 topics typical of the private equity sector (IPO, venture capital, investments, predictive analytics), which also find significant application in the M&A field thanks to the use of graph neural networks and advanced data analytics for process support.
- The sixth cluster (light blue) includes 21 elements and encompasses the use of natural language processing, typically for evaluating intangibles (which are inherently more qualitative than quantitative) and studying synergies.
- The seventh cluster (orange) includes 18 keywords and deals with the indirect effects of big data in terms of competition, privacy, and market dynamics.
- The eighth cluster (brown) includes 16 keywords related to the application of blockchain technologies, primarily in the legal and due diligence aspects of M&A. It is noteworthy that, among the three technologies, blockchain appears to be the least explored in terms of occurrences.
- The ninth cluster (pink) includes 15 topics related to the use of AI and big data to track and enhance communication of CEOs in the post-merger phase.
- The tenth cluster (violet) includes 15 topics focused on post-merger monitoring.

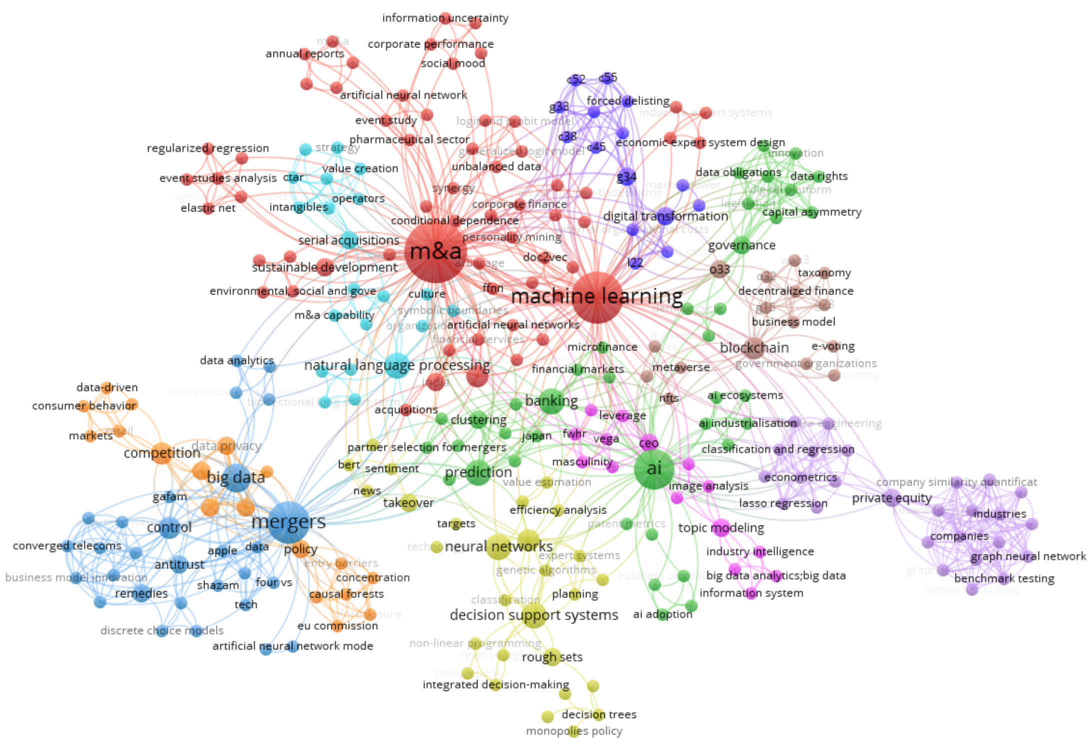


Figure 2.4: Topic network based on author's keywords.

Overall, a broad overview of applications emerges, which is explored in greater detail in the following section.

2.3 A framework of the current literature

Having analyzed the 85 selected articles, identified the topics explored in the literature, and established the main technologies investigated, it is now possible to determine the prominent themes in the implementation of advanced technologies within M&A processes.

To identify the themes, bibliographic coupling (Kessler, 1963) and content analysis of the examined articles were employed. The assumption is that articles exhibiting similar referencing patterns (citing similar sources) can be associated in terms of content and contribution to the literature. With a total of 184 connections (same documents cited in the references), the bibliographic coupling map (Figure 2.5) can be divided into four thematic clusters that represent 67% of the selected literature (57 articles out of a total of 85). The complete list of articles included in each cluster is provided in Appendix C.

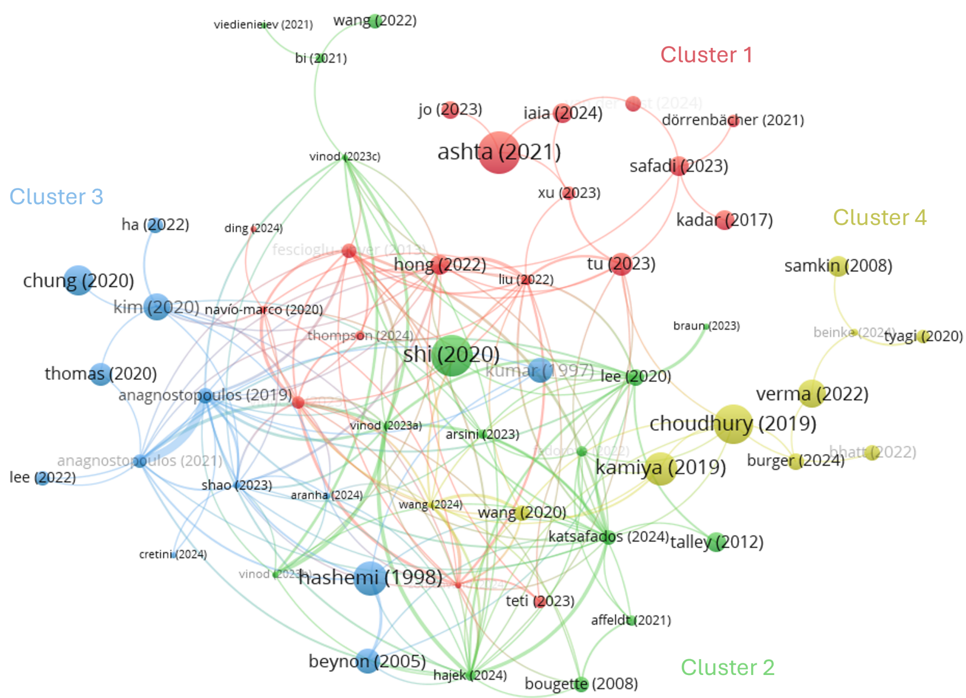


Figure 2.5: Bibliographic coupling map of thematic clusters.

It is challenging to delimit the precise focus of each cluster, as the low volume of production in this field results in many common themes. However, a thorough reading of the articles reveals that the first cluster places a strong emphasis on the more mature technologies, which are presented as game changers within the M&A

process, able to move it away from traditional approaches. In contrast, clusters 2, 3, and 4 depict advanced technologies as innovative tools available to a process that remains traditional. Additionally, clusters 3 and 4 tend to be more technology-specific, concentrating on the various applications of a single technology, while clusters 1 and 2 are more task-focused, sometimes exploring the application of technologies in a specific phase of the process in a technical manner. Table 2.8 provides a quick summary of the four identified clusters, while below a detailed account of the main contributions found in the literature is presented.

Table 2.8: Overview of the 4 thematic clusters identified.

Thematic cluster	Key focus	Technologies	Methods
Cluster 1: Technological transformations	Advanced technologies in M&A processes	Mainly AI and Big Data	Case studies
Cluster 2: Predictive insights	Prediction of M&A outcomes through data-driven approaches	Machine Learning	Econometric models, sentiment analysis
Cluster 3: Neural and deep learning applications	Emotional intelligence and social dynamics in M&A	Deep Learning, AI	Neural networks, computational linguistics
Cluster 4: Improving communication and collaboration	CEO communication styles and actors' collaboration	Blockchain, Machine Learning	Sentiment analysis, qualitative research

Overall, despite the thematic differences among the various clusters, a positive sentiment from the authors appears to be dominant within the abstracts, particularly for the last cluster (Figure B.1).

2.3.1 Cluster 1: Technological transformations

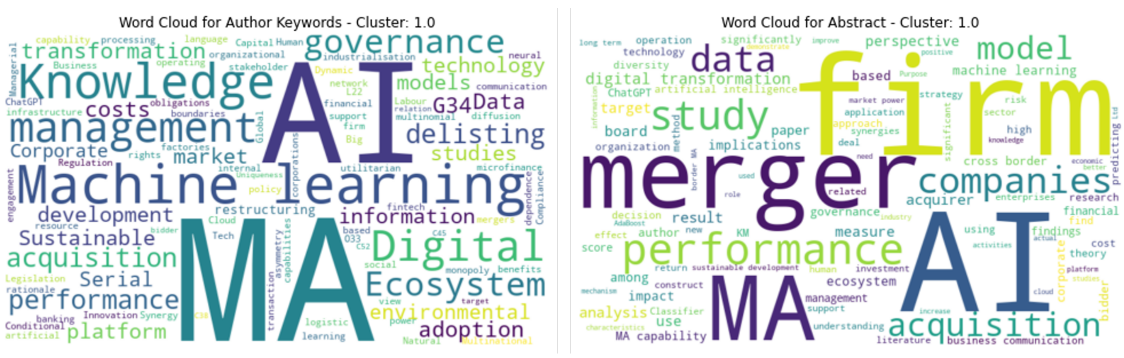


Figure 2.6: Word clouds for cluster 1 based on author keywords (left) and abstracts (right).

Comprising 18 articles with a total of 243 citations, the first cluster focuses (Figure 2.6) on the broad theme of the innovation brought by artificial intelligence in the M&A sector. Given the lack of developed research in this field, a common methodology for exploring the applications of AI in M&A is the use of case studies (Ashta and Herrmann, 2021; Tu and He, 2023).

Tu and He, 2023, Jo and D.-H. Park, 2023 demonstrate how the use of common AI tools in day-to-day operations and across all phases of the M&A process can have positive effects, reducing costs, shortening the required time, and improving overall outcomes. Overall, however, Iaia et al., 2024, highlights that AI still lacks human judgment and emotional intelligence, and remains a data-biased technology. For this reason, a fully automated process is not yet feasible. Instead, a collaborative approach should be considered, particularly for effective risk management (Ashta and Herrmann, 2021). Moreover, as processes evolve, so does regulation: the EU now conducts checks regarding acquired data rights and knowledge control, as digital monopolies may stifle innovation (Safadi and Watson, 2023; Kadar and Bogdan, 2017).

An interesting application is provided by Fescioglu-Unver and Tanyeri, 2013, who compares artificial neural networks and multinomial logit models as decision support tools in the strategic phase, identifying potential target companies based on their maximum deal success potential.

Zohrehvand, Doshi, and Vanneste, 2024, on the other hand, demonstrates how the use of the Synthetic Control (DISC) method combined with machine learning serves as a valuable tool for practitioners in supporting decision-making processes by evaluating the potential effects of strategic decisions and policies. This method enables the implementation of a data-driven approach to decision-making and has the advantage of not requiring large datasets.

2.3.2 Cluster 2: Predictive insights

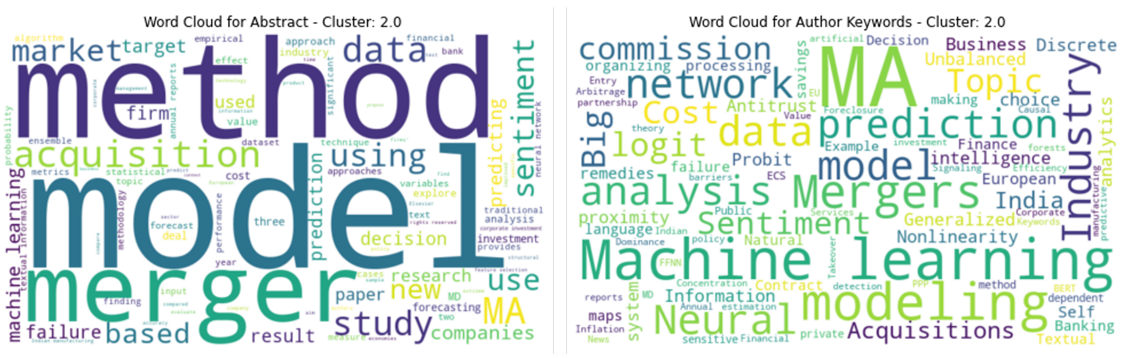


Figure 2.7: Word clouds for cluster 2 based on author keywords (left) and abstracts (right).

Unlike the first cluster, the second (comprising 16 articles with 167 citations) focuses on innovative methods for developing advanced forecasting methods in the

M&A decision-making process.

Citations in this cluster are primarily driven by Shi, G. M. Lee, and Whinston, 2014, a significant article in the M&A literature as it introduces a new "data-analytic approach to measure firms' dyadic business proximity". The proximity of firms in M&A transactions is of fundamental importance and is consistently correlated in the literature with performance and the overall success of the transaction. The article also provides another important application by extending the analytical model to big data, specifically for identifying startups (and more generally, targets) in acquisition and IPO processes. By incorporating proximity analysis into a platform, it transforms from a critical activity for the acquiring firm into a filter through which subsequent evaluation and due diligence efforts are focused only on ideal candidates.

Another significant contribution, although applied to the realm of public-private partnerships, is the work by Y. Wang and Tiong, 2022, in which the authors propose a Python-based model to assess the likelihood of failure in PPPs, thereby creating a useful tool for the pre-transaction phase to support the decision-making process. Similarly, K. Lee et al., 2020 addresses the challenges posed by unbalanced class datasets, which are common in M&A scenarios, but by utilizing a flexible neural network. The goal remains to facilitate decision-making through the development of more accurate forecasts that account for complex factors such as the influence of specific contractual elements and competitive dynamics.

2.3.3 Cluster 3: Neural and deep learning applications

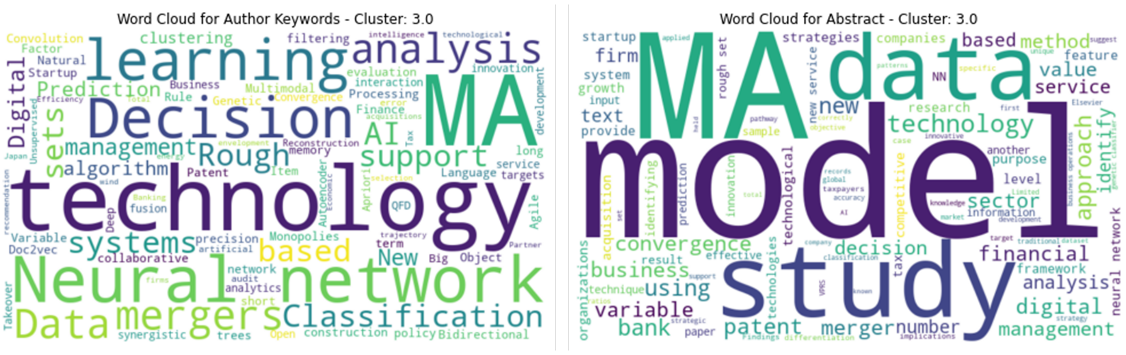


Figure 2.8: Word clouds for cluster 3 based on author keywords (left) and abstracts (right).

The third cluster consists of only 13 articles regarding the use of neural networks or advanced AI technologies to generate outcomes but has a total of 247 citations. Inevitably, this cluster overlaps with the previous one, as demonstrated in Figure 2.5 by the numerous connections between the two. Moreover, as highlighted in Chapter 1, neural networks and deep learning exhibit the ability to reason with good performance even on unstructured data, making them ideal tools for developing forecasts and predictions in the M&A sector.

Hashemi et al., 1998 represents one of the first applications of neural networks (NN) to reduce noise in the databases used for identifying potential candidates for M&A transactions, enhancing their effectiveness. Anagnostopoulos and Rizeq, 2019 continues this research, demonstrating that Artificial Neural Networks (ANNs) can significantly improve the accuracy of predicting merger targets compared to traditional linear regression models, particularly by identifying nonlinear relationships in data, which are typical in complex M&A scenarios. The main limitation is the need for sufficient data for effective calibration, however, this is partially alleviated today in certain sectors due to the availability of big data. An important extension of the model is achieved by adopting a more holistic approach that incorporates non-financial indicators, such as social media sentiment and operational metrics, into the predictive models.

Chung and Sohn, 2020 presents a deep learning model for the early identification of potentially valuable patents, once again positioning itself as an implementation in the strategic phase to support the decision-making process and evaluation. In the due diligence stage, C. Lee, 2021, proposes a deep learning approach for selecting taxpayers for audits, which can be applied in M&A to identify tax-related risks. In this case, the authors acknowledge the limitations of deep learning in terms of potential hallucinations and errors; therefore, the AI tool is used solely as a reporting mechanism, while the actual verification and certification remain the responsibility of human agents.

2.3.4 Cluster 4: Improving communication and collaboration

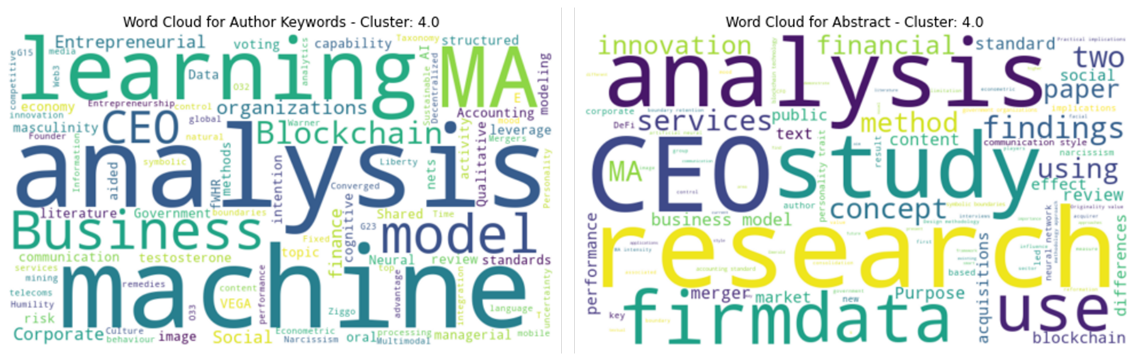


Figure 2.9: Word clouds for cluster 4 based on author keywords (left) and abstracts (right).

The fourth cluster is the smallest, comprising 10 articles with a total of 238 citations. Its focus is primarily on the use of qualitative approaches to understand and enhance M&A processes. One of the most significant qualitative aspects is the communication and emotions conveyed by CEOs during the transaction.

Several studies have explored the relationship between communication and performance (Q. Wang and Yiu Keung Lau, 2024; Choudhury et al., 2019), showing the existence of five distinct CEO communication styles that correlate with M&A outcomes. Overall, more dramatic communication styles may hinder major acquisitions, while narcissistic traits can initially benefit startup success but may lead to negative outcomes in later stages. Additionally, moods such as surprise and fear negatively impact acquirer performance, especially in small and uncertain contexts. In this context, advanced technologies are predominantly utilized in the research methods employed; however, they remain a partially explored potential implementation, as current generative AI models enable the creation of images, videos, text, and voice with precise emotions and behaviors. The possibility of controlling outgoing communications (or entirely generating them) with perfect sentiment appears to be an application we are approaching, and that could lead to higher success rates.

Two articles, however, address the use of decentralized structures in finance (Beinke et al., 2024) and the impact of blockchain on governmental organizations (Verma and Sheel, 2022), demonstrating the potential applications of this technology as identity certifiers, for secure document exchange, information certification, and data preservation. Nonetheless, within the selected literature, the theme of blockchain does not appear to be extensively researched, leaving avenues open for future exploration.

Chapter 3

Future research

Knowing the literature, it is now possible to add the professional perspective. This is introduced through consulting reports and discussions with industry professionals held during the last weeks of August and the beginning of September 2024. The main reports reviewed to evaluate potential discrepancies with the applications recognized in the literature are:

- "Transforming the M&A Process: The Current and Future Role of Artificial Intelligence", IMAA (Institute for Mergers, Acquisitions & Alliances), September 2023.
- "Global M&A Report 2024", Bain & Company, 2024.
- "Big data analytics in the context of M&A", Norton Rose Fulbright, August 2017.
- "Blockchain-based business models and M&A – an outlook", Rödl & Partner, October 2020.
- "The potential of blockchain and smart contracts in M&A", Clairfield International, March 2019.
- "Gen AI: Opportunities in M&A", McKinsey, May 2024.
- "How AI will impact due diligence in M&A transactions", EY, January 2024.
- "Top M&A trends in 2024", McKinsey, 2024.
- "Artificial intelligence and mergers and acquisitions. Observations from the frontlines and how to prepare for the coming shift", Deloitte, 2024

The analysis of these reports reveals both commonalities and divergences compared to the academic literature. First, as highlighted for the research by the topic analysis, there is a stronger emphasis on artificial intelligence, although Generative AI is frequently mentioned in working settings, a technology that is still nearly absent from the academic literature. Likely, less attention is given to blockchain, despite its greater prominence in professional contexts. The greater maturity of the concept of big data is confirmed, as advanced data analysis on large datasets is now almost integrated into the traditional process.

Regarding the topics, the pre-deal phase is also predominant in consultancy reports, with 6 out of 9 documents highlighting the potential of advanced technologies to support the decision-making process. This aligns with the current use of AI in M&A processes (Figure 3.1), where it is predominantly applied in the pre-deal phases. Furthermore, the interest of companies follows this direction, with firms seeking to implement AI primarily to reduce manual effort (78%) and accelerate timelines (54%), knowing that the pre-deal phase is the more time-constrained. Improving clarity, revenue, and regulatory compliance are perceived as lesser benefits according to companies (34%, 4%, 4% respectively, data from the Bain M&A Practitioners' 2024 Outlook Survey). Conversely, these aspects are considered predominant in academic research. This highlights a discrepancy, wherein research views advanced technologies as an opportunity to increase value, whereas companies perceive them just as efficiency tools rather than effectiveness enhancers. However, this aspect is less prominent from the perspective of major consultancy firms, which instead promote AI as a significant opportunity to increase the value generated.

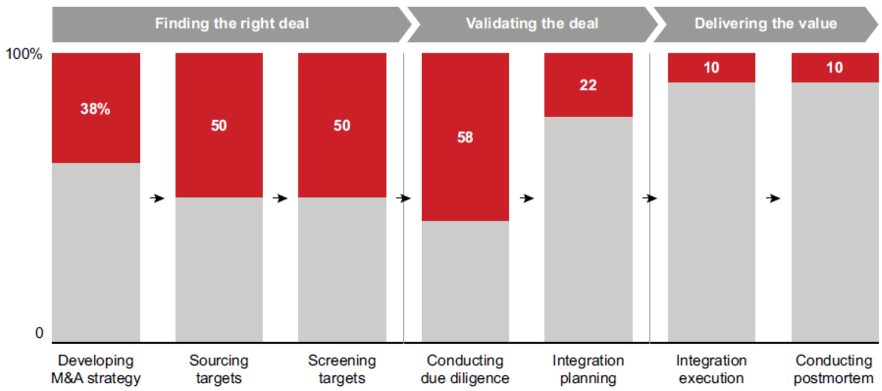


Figure 3.1: Percentage of M&A practitioners using generative artificial intelligence at each step (Siegal and Houston, 2024).

Consistent with academic research, a significant contribution of advanced technologies, due to their characteristics, can be found in evaluation procedures, aimed at increasing accuracy and the range of parameters considered. The reports place great emphasis also on the due diligence phase, often one of the most intensive stages with the greatest potential for automation, given its repetitive tasks, which follow defined rules. This emphasis, however, is not reflected in the academic literature, as demonstrated by the word clouds and thematic maps, where due diligence is only a minor topic and rarely mentioned.

Regarding the post-deal phase, while research usually focuses on a specific application, consultancy reports tend to remain vague; they emphasize the significant potential of AI, especially in combination with big data, in facilitating the integration of cultures, systems, and data, but without giving clear applications. A notable difference lies in the topics of communication and emotions: while academic research highlights the importance of these factors for the success of transactions, professional documents almost entirely omit this theme.

A significant white gap remains in the area of blockchain. Reports highlight how this technology, particularly smart contracts, could reduce interruptions and data loss throughout the process, however, the academic literature has yet to present relevant studies on the application of blockchain in the M&A domain. A second gap concerns the application of studies on emotions and communication from the employees' perspective. Research has traditionally focused on CEOs or CFOs to correlate emotions with performance, however, AI could hold great potential if utilized to track employee sentiment in the post-deal phase, ensuring well-being, engagement, and openness to change. Finally, big improvements could be obtained by mixing the technologies and applying them in the M&A, unlocking their real potential and balancing the drawbacks of the single technologies(S. Kumar et al., 2022).

From the perspective of the limitations in applying technology to M&A, both research and professional world are aligned, highlighting concerns regarding privacy, sensitivity to data biases, and security (Figure 3.2). However, the security concerns appear inconsistent with the limited attention given to blockchain, which offers notable advantages in this regard.

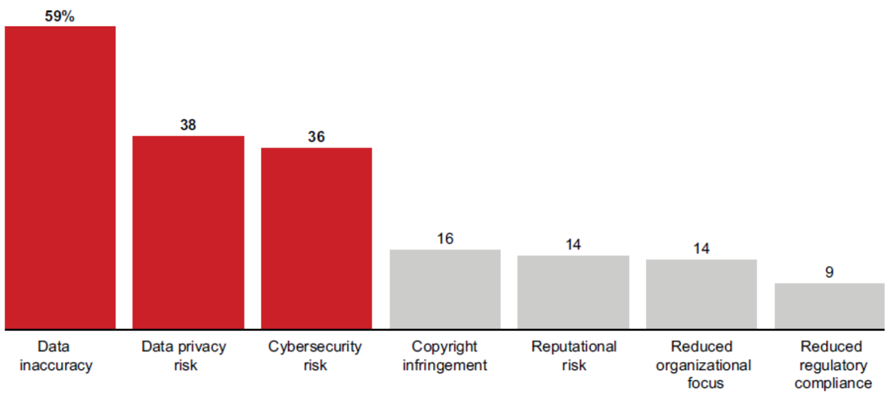


Figure 3.2: Most concerning risks of using generative artificial intelligence in the M&A process (Siegal and Houston, 2024).

Conclusion

When discussing advanced technologies, media, academic, and professional attention is currently focused on three main themes: artificial intelligence, blockchain, and big data. However, these topics are much more than mere trends; they are areas that have been the subject of research for years and, due to the results and performance achieved, are now game-changers across all sectors. A pressing issue in business contexts today is understanding how these technologies will alter traditional processes.

For extraordinary events, given the substantial investments involved and their limited repeatability, these technologies have yet to determine how they will impact the landscape. This study, therefore, focused on identifying possible evolutions in the M&A sector through bibliometric content analysis. From this analysis, four main findings have emerged.

First, the complexity of merger and acquisition operations and their dependence on numerous exogenous and endogenous variables have made the topic challenging to study comprehensively. As a result, academic research has developed over time in a siloed manner. However, the lack of a holistic perspective has limited research, particularly regarding innovation, leading books and the professional world to guide innovation more than academic research itself.

Second, despite a clear trend of increasing publication productivity, which remains limited compared to the widespread interest in research on these technologies, the current literature appears to have developed in a non-collaborative manner, with studies that rarely reference one another. This contributes to a body of literature that is difficult to navigate and poorly suited for future research, where even the most seminal articles are not leveraged to build new knowledge, necessitating the adaptation and recontextualization of research from other fields.

In an effort to structure the literature to facilitate future research, four main clusters have been identified, distinguished based on the prevailing focus shown and generating four primary research strands. These clusters are primarily divided according to the technology employed, meaning that there are no phases of the process that remain unaffected by technology; however, some technologies, such as blockchain, are less explored than others. Furthermore, an exception is the theme of communication and emotions in the post-merger context, which appears to have its own distinct and horizontal strand independent of technology.

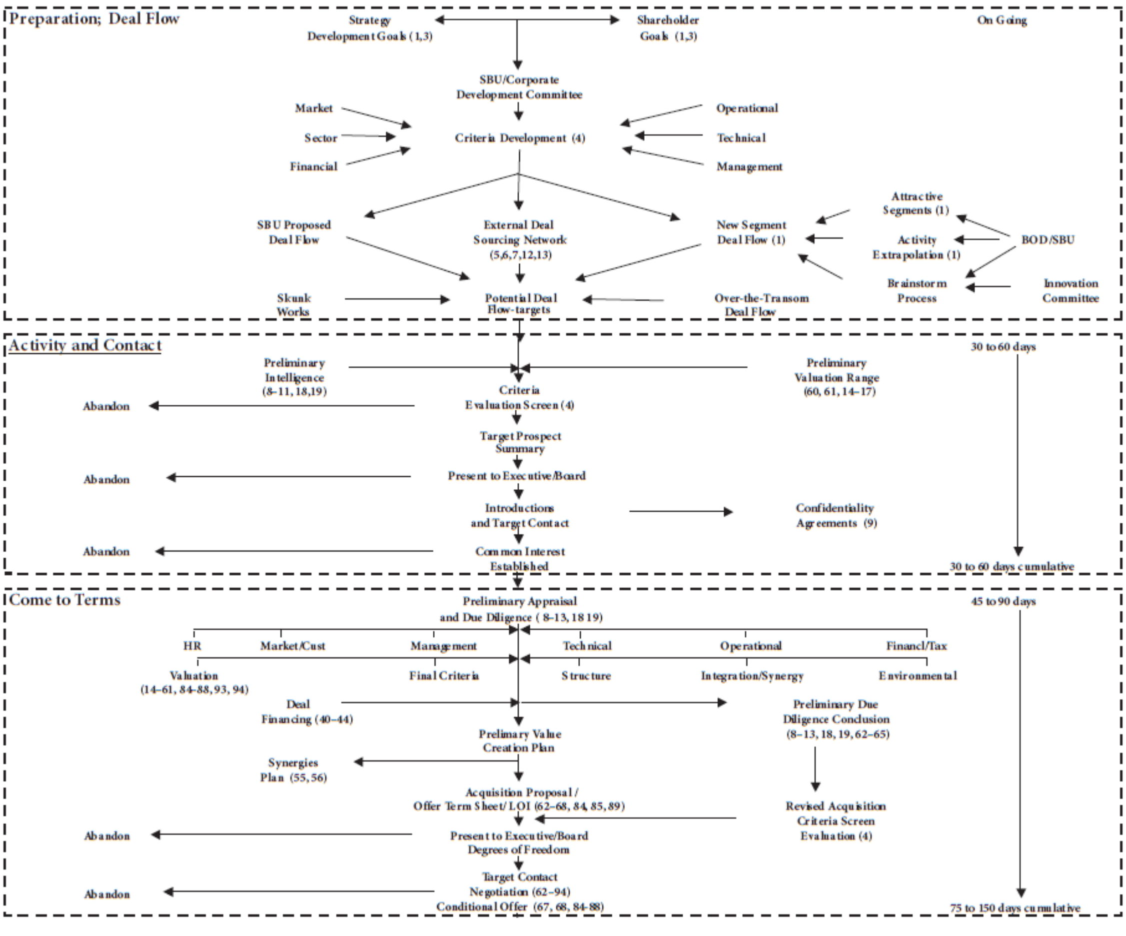
Finally, the comparison with current reports and opinions demonstrates how the professional and academic worlds operate independently in this field, missing opportunities that could arise from their collaboration.

Inevitably, the methodology employed has its limitations. There are three main limitations. First, by collecting literature from only one database, it is unavoidable that the dataset is not comprehensive, which could significantly distort the results. A multi-source approach would be more suitable for this purpose. Second, the search strings used are inherently limited: the M&A sector employs very common terms to identify relevant concepts; while including such terms in the searches would certainly capture all articles, it would also make the document set to be reviewed excessively large. Selecting articles using AI tools could help address this issue in future research.

In conclusion, if the question is whether M&A activities will continue to be labor-intensive, it remains too early to provide a definitive answer. However, it is evident that advanced technologies will serve as tools that support, rather than replace, human intervention. Human expertise and judgment remain predominant and essential for the successful completion of M&A transactions.

Appendix A

The M&A process



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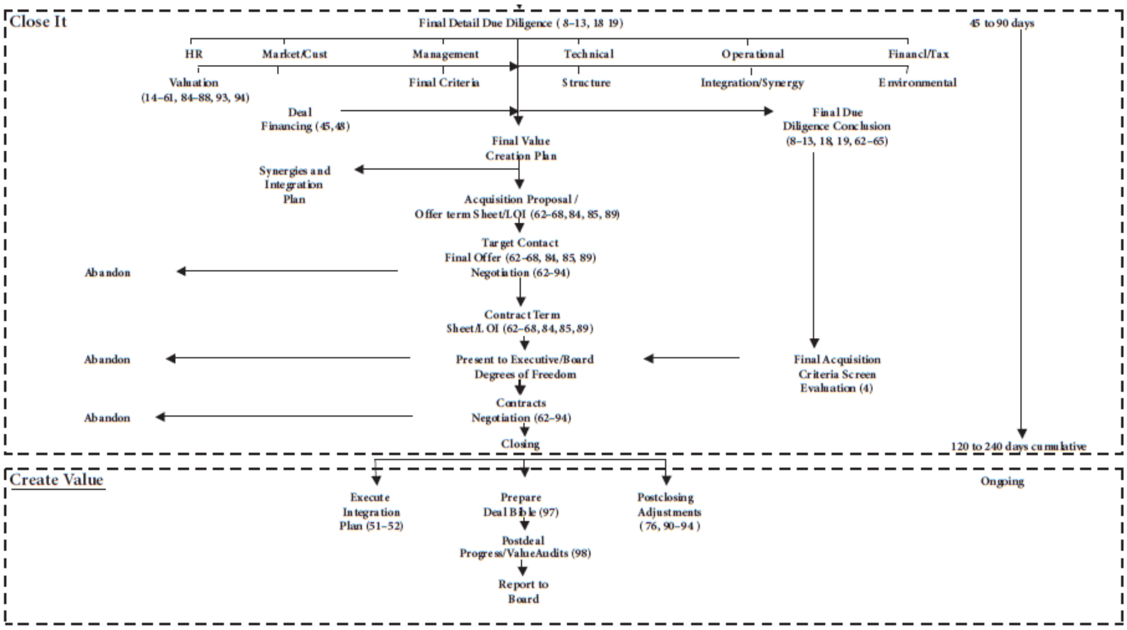

Figure A.1: The M&A process activity and stages map (Emott, 2012).

Appendix B

Python codes

Code for generating word clouds based on author keywords and abstracts for each cluster. Note that the special character "&" caused issues in generating the word clouds, so the term "M&A" was replaced with "MA".

```
import pandas as pd
from wordcloud import WordCloud
import matplotlib.pyplot as plt

# Upload csv
file_path = "C:/Users/Desktop/Database.csv"
df = pd.read_csv(file_path)

# Data chack and adjustments
df['Cluster'] = df['Cluster'].astype(str)
df_filtered = df[df['Cluster'].str.strip() != ""]

# Get cluster
clusters = df_filtered['Cluster'].unique()

# Word clouds generator
for cluster in clusters:
    # Word cloud by "Author Keywords"
    keywords_text = " ".join(keywords for keywords in
    df_filtered[df_filtered['Cluster'] == cluster]
    ['Author Keywords'] if pd.notna(keywords) and
    keywords.strip() != "")

    # Solve text error
    keywords_text = keywords_text.replace("M&A", "MA")

    # Word cloud generator
    keywords_wordcloud = WordCloud(width=700, height=400,
    background_color='white', max_words=100, contour_width=3,
```

```
    contour_color='steelblue').generate(keywords_text)

    # Show Word cloud
    plt.figure(figsize=(10, 5))
    plt.imshow(keywords_wordcloud, interpolation='bilinear')
    plt.axis('off')
    plt.title(f'Word Cloud for Author Keywords-Cluster:{cluster}')
    plt.show()

    # Word cloud by "Abstract"
    abstract_text = " ".join(abstract for abstract in
    df_filtered[df_filtered['Cluster'] == cluster]['Abstract'] if
    pd.notna(abstract) and abstract.strip() != "")

    # Solve text error
    abstract_text = abstract_text.replace("M&A", "MA")

    # Word cloud generator
    abstract_wordcloud = WordCloud(width=700, height=400,
    background_color='white', max_words=100, contour_width=3,
    contour_color='steelblue').generate(abstract_text)

    # Show Word cloud
    plt.figure(figsize=(10, 5))
    plt.imshow(abstract_wordcloud, interpolation='bilinear')
    plt.axis('off')
    plt.title(f'Word Cloud for Abstract - Cluster: {cluster}')
    plt.show()
```

Code for sentiment analysis based on the abstracts of the articles contained in each cluster. It is noteworthy that the number of abstracts is sometimes greater than the number of articles in the cluster. This discrepancy arises from the fact that the Distilled BERT model has a limit on the length of the texts that can be analyzed (512 tokens), therefore, longer abstracts were split into multiple segments.

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from transformers import pipeline, DistilBertTokenizer

# Import data
sentiment_file_path = r'C:\Users\Desktop\Cluster_Database.xlsx'
sentiment_df = pd.read_excel(sentiment_file_path)

# Initialize the tokenizer and sentiment analysis pipeline
tokenizer = DistilBertTokenizer.from_pretrained(
'distilbert-base-uncased-finetuned-sst-2-english')
```

```python
sentiment_pipeline = pipeline("sentiment-analysis")

# Function to split long abstracts
def split_long_abstracts(text, max_length=512):
    tokens = tokenizer.tokenize(text)
    split_texts = []
    for i in range(0, len(tokens), max_length - 2):
        split_texts.append(tokenizer.convert_tokens_to_string(tokens
        [i:i + max_length - 2]))
    return split_texts

# Perform sentiment analysis
sentiment_results = []
for index, row in sentiment_df.iterrows():
    abstracts = split_long_abstracts(row['Abstract'])
    for abstract in abstracts:
        if abstract:
            try:
                result = sentiment_pipeline(abstract)[0]
                sentiment_results.append({'Sentiment':
                result['label'], 'Score': result['score'],
                'Cluster': row['Cluster']})
            except Exception as e:
                print(f"Error")

# Create a DataFrame from sentiment results
sentiment_results_df = pd.DataFrame(sentiment_results)

# Count sentiment occurrences per cluster
sentiment_counts = sentiment_results_df.groupby(['Cluster',
'Sentiment']).size().unstack(fill_value=0)

# Set color palette for the plots
colors1 = ['salmon', 'lightgreen']
colors2 = ['lightgreen', 'salmon']

# Create the stacked bar plot for sentiment distribution by cluster
plt.figure(figsize=(12, 6))
sentiment_counts.plot(kind='bar', stacked=True, color=colors1)
plt.xlabel('Cluster', fontsize=14)
plt.ylabel('Number of Abstracts', fontsize=14)
plt.xticks(rotation=0)
plt.legend(title='Sentiment', fontsize=12)
plt.grid(axis='y')
plt.tight_layout()
plt.show()
```

```
confidence_df = pd.DataFrame({
    'Confidence': sentiment_results_df['Score'],
    'Sentiment': sentiment_results_df['Sentiment']
})
sns.set_theme(style="whitegrid")

# Create the density plot for confidence scores
plt.figure(figsize=(12, 6))
sns.kdeplot(data=confidence_df, x='Confidence', hue='Sentiment',
fill=True, common_norm=False, palette=colors2, alpha=0.5)
plt.xlim(0, 1)
plt.title('Density Curve of Confidence Scores by Sentiment',
fontsize=16)
plt.xlabel('Confidence Score', fontsize=14)
plt.ylabel('Density', fontsize=14)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.grid(alpha=0.7)
plt.show()
```

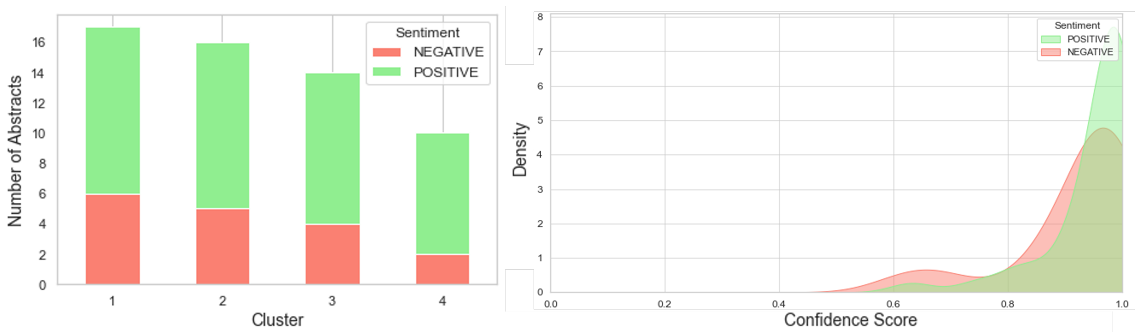

Figure B.1: Sentiment analysis results. Number of abstracts with positive or negative sentiment per cluster (left); density curve of the confidence score by sentiment (right).

Appendix C

Cluster articles

Table C.1: Detail of Cluster 1, consisting of 18 articles with a total of 243 citations.

Title	Author(s)	Year	Journal	Citations
Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance	Ashta A.; Herrmann H.	2021	Strategic Change	116
Can Digital Transformation Facilitate Firms' M&A: Empirical Discovery Based on Machine Learning	Tu W.; He J.	2023	Emerging Markets Finance and Trade	21
Supporting the implementation of AI in business communication: the role of knowledge management	Iaia L.; Nespoli C.; Vicentini F.; Pironti M.; Genovino C.	2024	Journal of Knowledge Management	15
Knowledge monopolies and the innovation divide: A governance perspective	Safadi H.; Watson R.T.	2023	Information and Organization	14
Application of Machine Learning Models for Predictions on Cross-Border Merger and Acquisition Decisions with ESG Characteristics from an Ecosystem and Sustainable Development Perspective	Hong X.; Lin X.; Fang L.; Gao Y.; Li R.	2022	Sustainability (Switzerland)	14
'Big data' and EU merger control - A case review	Kadar M.; Bogdan M.	2017	Journal of European Competition Law and Practice	14
AI in the Workplace: Examining the Effects of ChatGPT on Information Support and Knowledge Acquisition	Jo H.; Park D.-H.	2023	International Journal of Human-Computer Interaction	11
Big AI: Cloud infrastructure dependence and the industrialisation of artificial intelligence	van der Vlist F.; Helmond A.; Ferrari F.	2024	Big Data and Society	8
A comparison of artificial neural network and multinomial logit models in predicting mergers	Fescioglu-Unver N.; Tanyeri B.	2013	Journal of Applied Statistics	7
Digital Transformation, Firm Boundaries, and Market Power: Evidence from China's Listed Companies	Xu Y.; Li C.	2023	Systems	5
The effect of environmental, social and governance score on operating performance after mergers and acquisitions	Teti E.; Spiga L.	2023	Business Strategy and the Environment	4
M&A capability and long-term firm performance: a strategic management perspective	Vinocur E.; Kiymaz H.; Loughry M.L.	2023	Journal of Strategy and Management	4
Contemporary restructuring trends in European multinational corporations: rationale and impact on labour and workers' participation	Dörrenbächer C.; Geppert M.; Hoffmann A.	2021	Critical Perspectives on International Business	4
Unique bidder-target relatedness and synergies creation in mergers and acquisitions	Liu T.; Lu Z.G.; Shu T.; Wei F.	2022	Journal of Corporate Finance	3

Table continues on the next page.

On modeling acquirer delisting post-merger using machine learning techniques	Thompson E.K.; Kim C.; Kim S.-Y.	2024	Journal of Management Analytics	2
Serial acquirers' strategy in the telecommunications sector: Integration or indigestion?	Navío-Marco J.; Solórzano-García M.; Vicente-Virseda J.A.	2020	European Journal of International Management	1
Impact of board diversity on Chinese firms' cross-border M&A performance: An artificial intelligence approach	Ding S.; Du M.; Cui T.; Zhang Y.; Duygun M.	2024	International Review of Economics and Finance	0
Generalizing event studies using synthetic controls: An application to the Dollar Tree–Family Dollar acquisition	Zohrehvand A.; Doshi A.R.; Vanneste B.S.	2024	Long Range Planning	0

Table C.2: Detail of Cluster 2, consisting of 16 articles with a total of 167 citations.

Title	Author(s)	Year	Journal	Citations
Toward a better measure of business proximity: Topic modeling for industry intelligence	Shi Z.M.; Lee G.M.; Whinston A.B.	2020	MIS Quarterly: Management Information Systems	109
The measure of a MAC: A machine-learning protocol for analyzing force majeure clauses in M&A agreements	Talley E.; O'Kane D.	2012	Journal of Institutional and Theoretical Economics	14
Unbalanced data, type II error, and nonlinearity in predicting M&A failure	Lee K.; Joo S.; Baik H.; Han S.; In J.	2020	Journal of Business Research	10
Market structures, political surroundings, and merger remedies: An empirical investigation of the EC's decisions	Bougette P.; Turolla S.	2008	European Journal of Law and Economics	8
Machine learning in bank merger prediction: A text-based approach	Katsafados A.G.; Leledakis G.N.; Pyrgiotakis E.G.; Androutsopoulos I.; Fergadiotis M.	2024	European Journal of Operational Research	7
Public-Private Partnership Contract Failure Prediction Using Example-Dependent Cost-Sensitive Models	Wang Y.; Tiong R.L.K.	2022	Journal of Management in Engineering	6
Predicting M&A targets using news sentiment and topic detection	Hajek P.; Henriques R.	2024	Technological Forecasting and Social Change	3
Impact of MD&A sentiment on corporate investment in developing economies: Chinese evidence	Fedorova E.; Drogovoz P.; Nevredinov A.; Kazinina P.; Qitan C.	2022	Asian Review of Accounting	3
25 years of European merger control	Affeldt P.; Duso T.; Szücs F.	2021	International Journal of Industrial Organization	3
Prediction and visualization of Mergers and Acquisitions using Economic Complexity	Arsini L.; Straccamore M.; Zaccaria A.	2023	PLoS ONE	2
Forecasting mergers and acquisitions failure based on partial-sigmoid neural network and feature selection	Bi W.; Zhang Q.	2021	PLoS ONE	2
Literature Review on Characteristics and Prediction Modeling of Mergers and Acquisitions in India	Vinod V.; Sudarsanam S.K.	2023	Finance India	0
The application of feed forward neural networks to merger arbitrage: A return-based analysis	Braun D.; Han Y.; Wang H.E.	2023	Finance Research Letters	0
Predicting Acquisitions in the Indian Financial Services Sector	Vinod V.; Sudarsanam S.K.	2023	Finance India	0
Multiple models in predicting acquisitions in the Indian manufacturing sector: a performance comparison	Vinod V.; Sudarsanam S.K.	2023	Interdisciplinary Journal of Information, Knowledge, and Management	0
Ensemble Forecasting Methods in DCF Modelling of the Fair Value of Enterprises	Viedienieiev V.A.	2021	Universal Journal of Accounting and Finance	0

Table C.3: Detail of Cluster 3, consisting of 13 articles with a total of 247 citations.

Title	Author(s)	Year	Journal	Citations
A hybrid intelligent system for predicting bank holding structures	Hashemi R.R.; Le Blanc L.A.; Rucks C.T.; Rajaratnam A.	1998	European Journal of Operational Research	65
Early detection of valuable patents using a deep learning model: Case of semiconductor industry	Chung P.; Sohn S.Y.	2020	Technological Forecasting and Social Change	45
Recommendation of startups as technology cooperation candidates from the perspectives of similarity and potential: A deep learning approach	Kim H.J.; Kim T.S.; Sohn S.Y.	2020	Decision Support Systems	32
An illustration of variable precision rough sets model: An analysis of the findings of the UK Monopolies and Mergers Commission	Beynon M.J.; Driffield N.	2005	Computers and Operations Research	28
Financial decision support with hybrid genetic and neural based modeling tools	Kumar N.; Krovi R.; Rajagopalan B.	1997	European Journal of Operational Research	27
Convergence and digital fusion lead to competitive differentiation	Thomas A.	2020	Business Process Management Journal	21
Identifying new innovative services using M&A data: An integrated approach of data-driven morphological analysis	Ha S.; Geum Y.	2022	Technological Forecasting and Social Change	8
Confining value from neural networks: A sectoral study prediction of takeover targets in the US technology sector	Anagnostopoulos I.; Rizeq A.	2019	Managerial Finance	8
Deep learning-based detection of tax frauds: an application to property acquisition tax	Lee C.	2022	Data Technologies and Applications	7
Conventional and neural network target-matching methods dynamics: The information technology mergers and acquisitions market in the USA	Anagnostopoulos I.; Rizeq A.	2021	Intelligent Systems in Accounting, Finance and Management	5
Categorisation of mergers and acquisitions in Japan using corporate databases: a fundamental research for recommendation	Shao B.; Asatani K.; Sakata I.	2023	International Journal of Technology Management	1
Mergers and acquisitions, knowledge base and technological trajectories. An exploratory study in the wind energy sector	Cretini I.O.; Robert V.; Vázquez D.	2024	Innovation and Development	0
Mergers of public sector banks: Best partner selection using a data-driven approach	Aranha M.L.B.; Mahapatra M.; Jacob R.T.	2024	Finance Research Letters	0

Table C.4: Detail of Cluster 4, consisting of 10 articles with a total of 238 citations.

Title	Author(s)	Year	Journal	Citations
Machine learning approaches to facial and text analysis: Discovering CEO oral communication styles	Choudhury P.; Wang D.; Carlson N.A.; Khanna T.	2019	Strategic Management Journal	95
The face of risk: CEO facial masculinity and firm risk	Kamiya S.; Kim Y.H.A.; Park S.	2019	European Financial Management	58
Blockchain for government organizations: past, present and future	Verma S.; Sheel A.	2022	Journal of Global Operations and Strategic Sourcing	37
Adding scientific rigour to qualitative data analysis: An illustrative example	Samkin G.; Schneider A.	2008	Qualitative Research in Accounting & Management	17
The role of narcissism in entrepreneurial activity: a systematic literature review	Burger B.; Kanbach D.K.; Kraus S.	2024	Journal of Enterprising Communities	9
A Language-Based Method for Assessing Symbolic Boundary Maintenance between Social Groups	Bhatt A.M.; Goldberg A.; Srivastava S.B.	2022	Sociological Methods and Research	8
Does the interplay between the personality traits of CEOs and CFOs influence corporate mergers and acquisitions intensity? An econometric analysis with machine learning-based constructs	Wang Q.; Lau R.Y.K.; Yang K.	2020	Decision Support Systems	8
Merger control in the telecom industry: a landscape transformed	Tyagi K.	2020	Journal of Business Strategy	5
Breaking the chains of traditional finance: A taxonomy of decentralized finance business models	Beinke M.; Beinke J.H.; Anton E.; Teuteberg F.	2024	Electronic Markets	1
Social mood and M&A performance: An empirical investigation enhanced by multimodal analytics	Wang Q.; Yiu Keung Lau R.	2024	Journal of Business Research	0

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Anagnostopoulos, I. and A. Rizeq (2019). “Confining value from neural networks: A sectoral study prediction of takeover targets in the US technology sector”. In: *Managerial Finance* 45.10/11, pp. 1433–1457.

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