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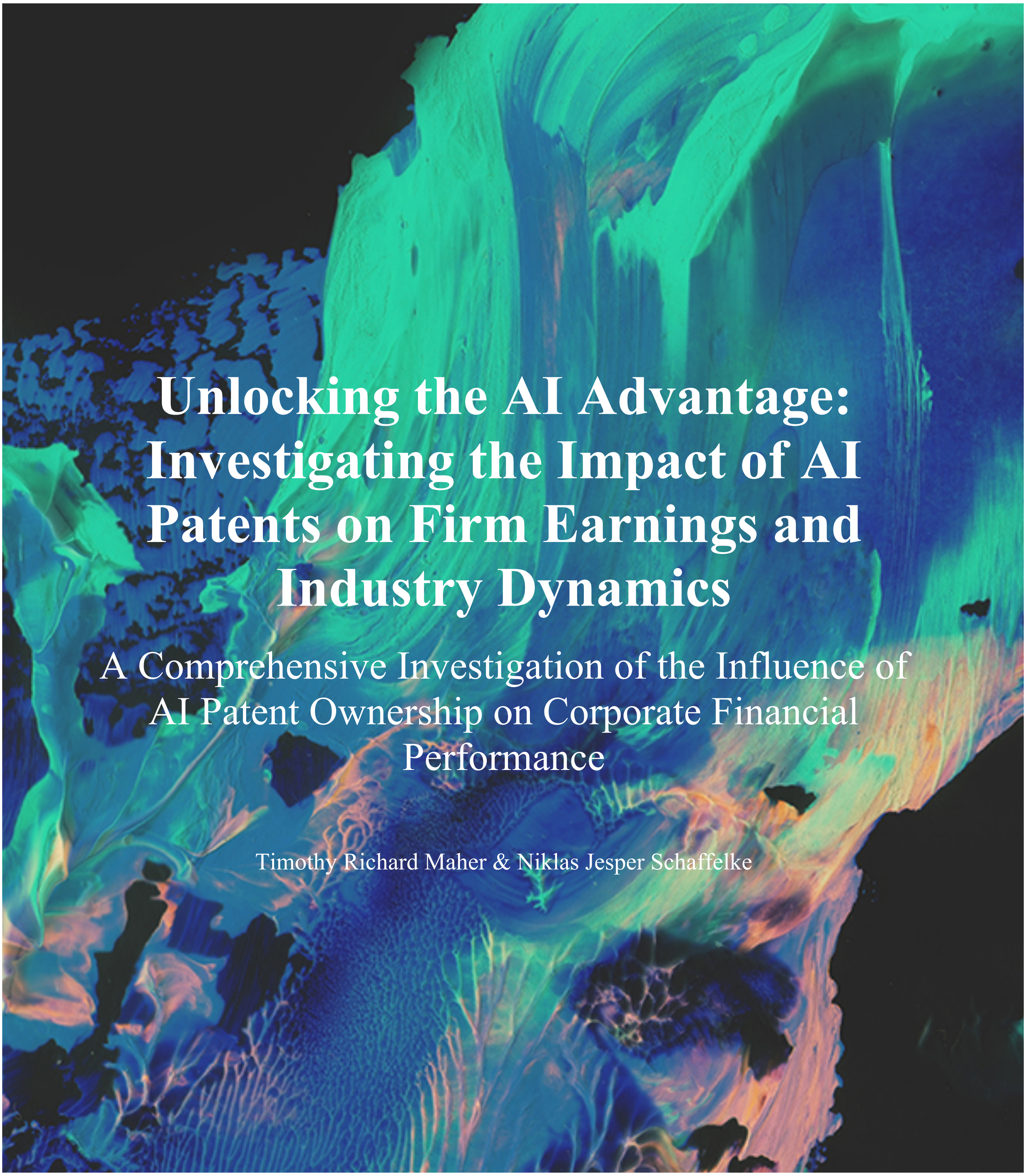

Unlocking the AI Advantage: Investigating the Impact of AI Patents on Firm Earnings and Industry Dynamics

A Comprehensive Investigation of the Influence of AI Patent Ownership on Corporate Financial Performance

Timothy Richard Maher & Niklas Jesper Schaffelke

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Supervisor: Norbert Steigenberger

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Abstract

This study aimed to investigate the relationship between AI patents owned by companies, company earnings, industry type, and company size. The research question guiding the study was: How do AI patents owned by companies affect their earnings, and do these effects differ across industries and company sizes?

Three hypotheses were developed to explore this question:

1. AI patents owned by companies have a positive effect on company earnings.

2. Patenting contributes more to a company's earnings in high-tech industries than in low-tech industries.

3. The effect of owned patents on earnings is less pronounced the larger a company is.

Using a quantitative approach, the researchers employed multiple linear regression analysis on a sample of companies across various industries and sizes. Data was collected from public databases, including patent records and financial statements.

The analysis led to the following conclusions regarding the three initial hypotheses:

Hypothesis 1: The findings indicate a positive but statistically insignificant relationship between AI patents and company earnings, suggesting that there may be a positive effect, but the analysis could not establish this relationship with statistical certainty.

Hypothesis 2: The study did not find enough evidence to support or reject the hypothesis that patenting contributes more to earnings in high-tech industries than in low-tech industries. This may be due to limitations in the dataset or the analysis approach employed.

Hypothesis 3: The influence of company size on the relationship between patents and earnings remains inconclusive. Although the results showed a positive relationship between the number of employees and earnings, the analysis did not provide sufficient evidence to determine the interaction effect between company size and patent ownership.

These inconclusive findings suggest that further research is necessary to better understand the relationship between AI patents, company earnings, industry type, and company size. Future studies could address the limitations of this study by incorporating more granular data on different industries, conducting industry-specific analyses, and employing alternative statistical methods or longitudinal data. This would help to enhance our understanding of the complex relationships between these factors and provide more actionable insights for businesses, investors, academics, and policymakers.

Keywords: *Artificial Intelligence, Patents, Financial performance, Innovation, Resource-based view*

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Umeå, Sweden

Timothy R Maher

Timothy Richard Maher

Niklas Jesper Schaffelke

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1 Introduction

1.1 Choice of Subject

Artificial intelligence (AI) has become an increasingly popular topic among businesses, researchers, and the general public (Haenlein & Kaplan, 2019; Brynjolfsson & McElheran, 2016; Cockburn et al., 2018), with increasingly ambitious declarations regarding its potential. Companies in various business sectors are investing vast amounts of funds into AI research and development (R&D) (Rosenbush, 2022), striving for a possible competitive advantage. With the increasing interest in AI from businesses in various industries, the possible correlation between the financial success of companies and their investment in research and development of artificial intelligence has garnered the interest of the authors of this thesis. With AI rapidly permeating various industries and changing the way we live and work, it is important to understand the relationship between investment into AI R&D and a company's success. Many companies seem to believe that artificial intelligence will somehow increase the company's performance, however, is there a scientific consensus that this relationship holds true? Due to its relevance and timeliness, the topic that was chosen for this thesis regarding the question of how research and development of artificial intelligence impacts business outcomes. The objective of this study is to investigate the correlation between the number of AI patents and the financial success of companies, as the number of AI patents might be a potential indicator of a company's investment in AI R&D. Furthermore, this thesis will analyze, if companies in certain industries benefit more from investing into AI research. The authors believe to provide valuable insights into the impact of AI investments on corporate financial performance. The hypothesis is that there is a correlation between the number of AI patents and the financial outcome of companies; this will be tested by regression analyses and other appropriate statistical methods.

1.2 Topic Background

Over recent decades, artificial intelligence (AI) has gained significant importance due to substantial advancements in areas like machine learning, computer vision, and natural language processing (Haenlein & Kaplan, 2019, p. 8). Such progress has led to the development of sophisticated AI systems capable of executing complex tasks and making decisions, which were once believed to be exclusive to human cognition (Zekos, 2021, p. 364). AI is expected to play a critical role in shaping the future of various industries, including business administration (Zekos, 2021, p. 349).

Business administration involves numerous activities such as managing operations and finances, devising and executing strategies, and handling human resources (Roetzel, 2019, p. 481). AI can impact these areas by automating routine tasks, offering actionable insights, and enhancing decision-making processes (Sutton et al., 2016, p. 66). AI-powered systems can analyze vast amounts of data to detect patterns and trends, resulting in more accurate and efficient decision-making (Zheng et al., 2019, p. 916). Moreover, AI can help organizations better understand and engage with customers, increasing customer satisfaction and improving relationships (Cheng & Jian, 2021, p. 260; Ruan &

Mezei, 2022, p. 7). OpenAI's ChatGPT model is a prime example of AI's potential to significantly impact companies and their offerings (Dotan, 2023). The model, its applications, and the subsequent response from businesses, the public, and governments demonstrate the extent to which AI can affect the corporate and social landscape (Dotan, 2023; van Dis et al., 2023, p. 224).

Previous research has explored AI's impact on various aspects of business administration, indicating that AI can greatly enhance the efficiency and accuracy of processes in these areas. This leads to cost savings for organizations and increased competitiveness (Acemoglu & Restrepo, 2019, p. 21). However, there are still significant gaps in understanding how AI should be effectively incorporated into organizations within the business administration field (Zekos, 2021, p. 136). This can be attributed to the complex and dynamic nature of AI systems, which continually evolve as new technologies and algorithms emerge. Additionally, ethical concerns regarding AI, such as potential job loss and privacy implications, have been raised (Zekos, 2021, p. 244, 403). Effective integration of AI into business administration necessitates the management of risks associated with AI while capitalizing on its benefits.

Further research has demonstrated AI's ability to automate non-routine cognitive tasks and replace human involvement in specific economic activities (Acemoglu & Restrepo, 2019, p. 21). Effectively integrating AI into business administration demands comprehensive understanding of the technology and careful consideration of ethical implications and organizational capabilities needed to implement AI systems (Zekos, 2021, p. 383).

AI not only has the potential to enhance the current economy by increasing efficiency but also to transform it entirely by serving as a new, all-encompassing tool for invention (Cockburn et al., 2018, p. 4). This could fundamentally change the way innovation occurs and the structure of research and development (R&D). Present research trends in AI reveal a significant increase in individual companies engaged in AI research and development for various applications (Brynjolfsson & McElheran, 2016, p. 137; Cockburn et al., 2018, p. 15). This surge in activity is believed to be driven by the anticipation of future market dominance by these companies (Cockburn et al., 2018, p. 15).

The growing interest in AI research and development signifies the potential transformative impact of AI on business administration and the economy as a whole. As companies strive to establish a competitive edge in the market, they invest in AI technologies to gain a foothold in this rapidly evolving field. This heightened level of engagement in AI R&D could lead to groundbreaking innovations that reshape industries and redefine the way businesses operate.

However, the rapid adoption of AI technologies also raises concerns about potential negative consequences, such as increasing income inequality, job displacement, and privacy issues (Acemoglu & Restrepo, 2019, p. 21; Zekos, 2021, p. 244). To address these challenges, policymakers, businesses, and researchers must collaborate to create strategies for the responsible and ethical implementation of AI in business administration. This may include retraining and upskilling programs for workers, the development of regulations and guidelines to protect privacy, and fostering a culture of transparency and accountability in AI deployment.

AI has the potential to significantly impact business administration by automating tasks, providing actionable insights, and improving decision-making processes (Acemoglu & Restrepo, 2019, p. 21). Despite the numerous benefits, there are still gaps in understanding how to effectively integrate AI into organizations and concerns about the ethical implications of AI adoption. Further research and collaboration among stakeholders are needed to ensure that AI is responsibly and effectively implemented in the field of business administration, ultimately leading to a more innovative and efficient economy.

1.3 Problem Background

The advancement of AI technology highlights the significance of research and development investment into artificial intelligence (European Commission, 2020, p. 3). Additionally, companies that invest in AI R&D could establish state-of-the-art technologies, which can allow them to develop proprietary AI technologies that can be protected by patents and might grant them a competitive edge (European Commission, 2020, p. 22). Patent protection is crucial for safeguarding proprietary technologies generated from R&D efforts. By obtaining patents, companies can restrict others from using their technologies without authorization and license their technology to third parties (Großmann et al., 2016, p. 316). This can provide a significant source of revenue for companies and can also help to ensure that they retain their competitive advantage (Hilty et al., 2021, p. 61). Furthermore, employing AI R&D can assist companies in differentiating themselves from their competitors and establishing a reputation for innovation and expertise in the field of AI, particularly in industries significantly impacted by AI such as finance, healthcare, and manufacturing (Mhlanga, 2020, p. 10; Li et al., 2017, p. 92; Liu et al., 2021, p. 8).

The growth and development of the artificial intelligence field holds the potential to provide advantages for companies, including the promotion of their innovations. One significant factor in achieving these benefits is the utilization of the patenting process. The study conducted by Acs et al. (2002, p. 1077) evaluated the reliability of using patent data as a proxy for proprietary innovation data. The results of the study demonstrated that patent data can be relied upon as a proxy for measuring innovation. Further, subsequent studies conducted by Ponta et al. (2021, p. 90) confirmed the reliability of using patent data as a metric for assessing innovation performance.

However, obtaining patents for AI technologies can pose challenges. The rapidly developing field of AI and the evolving legal definitions of patentable AI technologies are factors that make the process of obtaining patents complex and time-consuming (Hilty et al., 2021, p. 56). AI technologies often involve complex algorithms and systems that can be difficult to describe in a way that meets the requirements for a patent. It can be challenging to demonstrate that the invention is new and non-obvious, as well as to describe the specific invention in sufficient detail to allow someone skilled in the field to understand how to make and use it (Hilty et al., 2021, p. 54). In some cases, AI technologies may also involve trade secrets or proprietary information, making it difficult to disclose enough information to secure a patent while still protecting the technology from being copied (Hilty et al., 2021, p. 61).

Patents are widely considered as early indicators of innovation, as they are typically applied before a product utilizing the invented technology, procedure, or formulation is introduced into the market (Benson & Magee, 2015, p. 11; Fankhauser et al., 2018, p. 5). As a result, they serve as a source of early predictions for new technologies. Despite uncertainties regarding the quality of patents, studies often rely on the simple application data of patents, such as the number of patents filed, to compare regions or companies in terms of their innovative capabilities (Acs et al., 2002, p. 1078). However, it is also recognized that not all inventions result in successful market innovations. In fact, a small proportion of inventions ultimately achieve commercial success (Roberts, 2007, p. 39). Some studies have reported a positive correlation between innovation and growth (Geroski & Toker, 1996, p. 154; Yasuda, 2005, p. 12), while others have found no significant impact (Bottazzi et al., 2001, p. 9; Lööf and Heshmati, 2006, p. 6). Furthermore, they are studies that have reported a negative relationship between innovation and growth (Brouwer et al., 1993, p. 156; Freel & Robson, 2004, p. 567).

1.4 Purpose

This thesis aims to conduct a comprehensive analysis of the financial benefits related to patenting AI technology for companies. The primary goal is to perform an extensive statistical analysis to determine the financial advantages of investing in artificial intelligence research and to identify other factors that may have an impact on these benefits. Additionally, this study aims to contribute to the innovation performance measurement literature by building upon previous research, such as the work conducted by Ponta et al. (2021).

The research hypothesis proposes a correlation between the number of AI patents and the financial success of companies. To test this hypothesis, regression analysis and other relevant statistical methods will be utilized to examine the relationship between the number of AI patents and various financial metrics, including revenue, profit, and total assets. Furthermore, the study will investigate whether companies in specific industries or different company sizes derive greater benefits from patenting AI technology. Data for this research will be collected from preexisting databases, specifically the patent database DEPATIS and Orbis Europe, a database containing financial information on European companies.

The outcomes of this research will have significant implications for the AI investment strategies of companies and investors. The results will provide valuable insights into the impact of AI patenting on companies' financial performance, helping them make informed decisions concerning AI investments. Moreover, the findings will inform policymakers about the importance of AI investment for economic growth and the development of AI technologies.

This thesis seeks to enhance the current understanding of the relationship between AI investment and financial performance, offering practical guidance for companies and investors contemplating AI investments. The results of this research will assist in shaping future innovation and investment in AI technologies, ultimately helping companies achieve greater financial success. By examining the impact of patenting AI technology on a firm's financial performance, this study will deliver valuable insights that can influence decision-making processes and investment strategies. Consequently, companies, investors, and policymakers will be better prepared to comprehend the significance of AI investment for economic growth and the development of AI technologies.

1.5 Research Question

The decision to investigate the correlation between the earnings of companies and their patenting activity towards AI has been prompted by multiple factors. First and foremost, there has been a marked increase in corporate investments in AI R&D, with numerous industry leaders making substantial commitments towards the development of AI capabilities (Rosenbush, 2022). This pattern suggests a potential relationship between financial prosperity and AI R&D investments. Financially successful companies may possess more resources to allocate towards AI R&D endeavors, creating a landscape where wealthier firms are more likely to invest in AI technologies.

Furthermore, it is crucial to evaluate the merits of allocating significant resources towards AI in terms of the resulting monetary gains for firms. AI holds the promise of creating considerable value for businesses, with the potential to revolutionize industries and yield competitive advantages. However, alongside these benefits, there are potential risks, ethical considerations, and costs associated with R&D that must be accounted for. As a result, it is vital to conduct a comprehensive cost-benefit analysis of investing in AI, considering both the potential financial gains and the costs and risks that accompany AI investments.

Considering these motivating factors, the current study aims to address several research questions to gain a deeper understanding of the implications of AI patents on firm earnings. The research questions are:

1. To what extent do AI patents owned by companies influence their earnings?

2. How does the impact of owned patents on firm earnings differ between high-tech and low-tech industries?

3. How does company size moderate the relationship between owned patents and earnings?

By examining the relationship between AI patents and earnings, the study seeks to determine if investments in AI patents result in tangible financial benefits for companies. The second question seeks to explore if the influence of AI patents on earnings is consistent across different industries, or if certain industries benefit more from AI patenting than others. The third question investigates whether the correlation between AI patents and earnings is dependent on the size of a firm, as larger firms may have more resources to leverage AI technologies effectively.

By addressing these research questions, the study aims to provide valuable insights into the potential benefits and risks associated with investing in AI R&D. Ultimately, these insights will help inform future investment decisions and guide businesses in navigating the rapidly evolving landscape of AI technologies.

1.6 Expected Results

The proposed study aims to examine the relationship between the number of AI patents held by companies and their financial success. With artificial intelligence's growing popularity, comprehending how investing in its innovation can bolster organizational outcomes has become increasingly imperative for companies seeking success. This study seeks to investigate the correlation between the number of AI patents and financial success as a potential indicator of a company's investment in AI development.

The study will use regression analyses and other appropriate statistical approaches to investigate the relationship between the number of Al patents and company financial success. The study’s findings are intended to provide significant insights into the influence of Al investment on company financial performance.

Should the hypothesis be supported, the results would suggest that companies that invest in AI through holding patents are more likely to experience financial success. Conversely, a lack of correlation between the number of AI patents and financial success would indicate that other factors may have a greater impact on a company's financial performance.

In either case, the findings of this study will make a significant contribution to the scientific community by providing an empirical examination of the relationship between AI patents and financial success. Additionally, these findings will be useful not only for businesses, but also for policymakers, and investors. Moreover, they could inform future research in this area and provide a foundation for developing strategies for effective AI R&D investment.

1.7 Delimitations

When conducting research, it is critical to clearly define the study's boundaries or delimitations. Researchers can provide a more accurate and reliable interpretation of their findings if they acknowledge these limitations. The limitations of this study, which focuses on the relationship between AI patents and firm performance in Europe between 2010 and 2022, will be discussed in this section.

The geographic scope of this study is one of its limitations. The researchers have chosen Europe as the geographic area of interest. This decision was made for practical reasons, as obtaining and analyzing data on a global scale would be difficult and therefore time-consuming and, after discussion, beyond the given time frame. However, because of this limitation, the findings may not be applicable to companies outside of Europe. Furthermore, the findings may not be transferable to other regions with different economic, political, and legal contexts, especially if patent laws and enforcement thereof differ significantly.

Another limitation of the research is the time frame. The researchers have chosen to concentrate on the years 2010 to 2022. This time frame was chosen because it corresponds to the rise of AI technology and its growing importance in the business world (European Patent Office, 2023). However, because of this decision, the impact of AI patents on firm performance in earlier or future periods are not investigating. Furthermore, factors that influence the relationship between AI patents and firm performance in previous years may differ from those in subsequent years.

The sample size is a third limitation of the study. The researchers chose to examine a sample of approximately 340 European companies. This sample was chosen based on the presence of AI patents. However, this sample size may not be representative of all European companies with AI patents. Other companies that hold AI patents but were not included in our sample may have different characteristics that influence the relationship between AI patents and firm performance.

The definition of firm performance is a fifth limitation of the study. The researchers chose EBIT as a measure of company performance because it is a metric that can be used to compare companies that may face different interest rates and taxes, as this may be the case due to the different size and location of companies in this study. However, other financial success indicators, such as return on investment or stock price, could be considered as well. The use of EBIT may thereby limit the applicability of our findings to companies that prioritize profitability over other financial objectives.

The measurement of Al patents held by companies is the subject of the sixth limitation of the study. Instead of patent applications, the researchers have chosen to base the analysis on patents granted. However, this statistic might not be a perfect reflection of a firm's innovation and research activity. Rather than being truly innovative, companies may file patents to protect their intellectual property or for strategic reasons. A company's innovation efforts can also be captured by other innovation metrics, such as R&D spending or the number of articles published in trade journals.

2 Artificial Intelligence, R&D and Patents

2.1 Artificial Intelligence - a Definition

Artificial intelligence is a relatively new area of research in the field of science, as research only began in the 1950s (Russel & Norvig, 2016, p 1.). There are different approaches and ways of looking at the definition of artificial intelligence, because even the definition of intelligence from the perspective of psychology, neuroscience and biology differs greatly (Kirste & Schürholz, 2019, p. 21). Although AI has become a perennial topic in many areas of society and business in recent years (Zekos, 2021, p. 349), to date there is no uniform or universally applicable definition for the term "artificial intelligence". However, a variety of definitions exist that are intended to describe artificial intelligence. One of the first definitions came from McCarthy (1955), who is considered one of the pioneers of artificial intelligence, and described the term "artificial intelligence" as follows:

"How to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves (McCarthy, 1955, p. 2)."

Over the years, different branches of AI have emerged and different approaches to defining AI have been developed in the literature:

"… defined as a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation (Haenlein & Kaplan, 2019, p. 15)."

"Artificial intelligence, or AI, is the field that studies the synthesis and analysis of computational agents that act intelligently (Poole & Mackworth, 2010, p. 3)."

The definitions provided above demonstrate that artificial intelligence is a multifaceted concept that presents challenges in terms of providing a precise definition. However, one defining characteristic is the ability to exhibit intelligent behavior. An intelligent machine, like a human, should exhibit intelligent behavior. This ability essentially distinguishes human intelligence from machine intelligence. Machine learning as a subfield of artificial intelligence will also be discussed later in this section. This subfield revolves around understanding the mechanisms of thinking and intelligent behavior and implementing this ability in machines. The attempt is to develop a system that can independently handle complex problems and respond to its environment, similar to human decision-making and rational action (Kirste & Schürholz, 2019, p. 21).

There are many ways to describe the heterogeneous research field of AI and its many subcategories. Some approaches deal with the problems that arise on the way to intelligence of computer systems, others with the solutions to these problems, and still others with the comparisons to human intelligence (Wittpahl, 2019, p. 21).

For the following parts of this study, the authors refer to the following definition of artificial intelligence: At the heart of artificial intelligence lies the capability to independently process vast amounts of data, identify patterns within it, and utilize these patterns to make decisions and predictions without external guidance. This autonomous decision-making ability is a defining feature of artificial intelligence, allowing machines to operate and learn in ways similar to humans (Kreutzer & Sirrenberg, 2019, p. 9).

2.2 Historical context - The beginnings of Artificial Intelligence

Artificial intelligence as an independent field has existed since the mid-twentieth century. In the 1930s, Kurt Gödel, Alonso Church, and Alan Turing laid the foundation for logic and theoretical computer science (Church, 1936; Gödel, 1931; Hadley, 2008, p. 3-8; Turing, 1937). In the 1940s, important insights were gained by McCulloch & Pitts (1943), and Hebb (1949), and the first mathematical models for neural networks were developed (Rosenblatt, 1958, p. 387-388). Neuroscience provided a decisive impetus. With the further development of programmable computers in the 1950s, Alan Turing explored in his study "Computing Machinery and Intelligence" whether machines are capable of thinking like humans (Turing, 1950). The Turing Test, also known as the Turing Test for intelligence, was proposed as a way to evaluate a machine's ability to exhibit intelligent behavior equivalent to, or indistinguishable from, that of a human (Turing, 1950, p. 433). The basic idea of the Turing Test is to have a human judge engage in natural language conversations with two entities: another human and a machine, without knowing which is which (Turing, 1950, p. 446). If the judge cannot reliably distinguish between the human and machine based on their responses, then the machine is said to have passed the Turing Test and demonstrated human-like intelligence. The test has been a controversial topic in the field of artificial intelligence since its inception, with many researchers arguing that it is an inadequate measure of true intelligence (Castelfranchi, 2013; Dougherty et al., 2006). Nonetheless, it has been a useful benchmark for evaluating natural language processing systems and has inspired further research into AI and machine learning.

In the following years, Newell and Simon achieved a breakthrough in computer symbol processing (McCorduck, 2004, p. 123-125, Russel & Norvig, 2016, p. 109), and McCarthy developed a programming language specifically for processing symbolic structures (Russel & Norvig, 2016, p. 19). The 1956 historic Dartmouth Conference served as a platform for the presentation of thinking systems that understand their environment and flexibly respond to it (Russel & Norvig, 2016, p. 17). This conference is considered the birthplace of the discipline of artificial intelligence. Numerous further technical achievements in symbol processing followed. The subsequent era is characterized by increasingly powerful computers and mathematically modeled neural networks that could learn tasks through training examples that previously had to be programmed with great effort (Russel & Norvig, 2016, p. 18-24). In practical terms, this meant that systems could identify people based on portrait photos through pattern recognition and the ability to recognize similarities (Russel & Norvig, 2016, p. 28).

Milestones in the development of AI include the victory of the chess computer Deep Blue over the reigning world champion Garry Kasparov in 1997 (Russel & Norvig, 2016, p. 185) and the victory of IBM's Watson computer in the trivia show Jeopardy in 2011 (IBM, 2012). The ability to understand irony, decode abstract statements, access targeted knowledge, and make quick decisions enabled the victory in 2011. In 2016, AI achieved another triumph, namely the victory of the AI system AlphaGo in the game "Go" (DeepMind, 2016). Deep-learning algorithms enabled not only the analysis of thousands of moves, but also the neural network to train itself through trial and error (Tegmark, 2017, p. 115). Since then, AI has arrived in the age of autonomous robots and the Internet of Things, making AI more visible in everyday life.

Artificial Intelligence is now more interdisciplinary than ever, drawing on insights from logic, operations research, statistics, control engineering, image processing, linguistics, philosophy, psychology, and neurobiology (Russel & Norvig, 2016). Given the rapid pace of technological progress in recent years and decades, some experts in the field of artificial intelligence believe that within the next 50 years there will be artificial intelligence that is at least the equal of humans in most tasks (Russel & Norvig, 2016, p. 12). Regarding this, there are concerns about the hypothetical future point of technological singularity (Kurzweil, 2005). The term technological singularity means the point in time at which machines through artificial intelligence improve themselves at such a speed that they accelerate technical progress to an extent that does not allow a prediction of the future of humans and humanity anymore (Vinge, 1993, p. 1). It's a theoretical concept that describes a hypothetical point in the future where artificial intelligence becomes so advanced that it surpasses human intelligence in a way that we can't even comprehend. Some theorists believe that machines will develop their own consciousness and make decisions independently without human intervention. This could be a positive outcome, where AI solves many of the world's problems and leads to a utopian society. However, it could also be a negative outcome where AI becomes a threat to humanity and causes significant harm.

The idea of a technological singularity remains a hypothetical concept, and many experts disagree on the likelihood and timeframe of its occurrence (Goertzel, 2007, p. 1162). Nevertheless, it is an important topic of discussion as we continue to develop and integrate AI into our lives.

In conclusion, artificial intelligence is a rapidly evolving field with many potential benefits and challenges. While AI has made significant progress in recent years, there is still much work to be done to fully understand and harness its potential. As we continue to develop and use AI, it is essential that we manage this technology responsibly and ethically, consider its potential impact on society, and ensure that its development and use are in line with human values and interests. In this way, we should ensure that AI serves to enhance and expand human capabilities rather than replace or harm them.

2.3 Advantages and Potential Benefits of AI

Artificial intelligence (AI) is anticipated to substantially influence the future of work (Frey & Osborne, 2017, p. 5). Many experts argue that AI will generate various new job opportunities (McAfee & Brynjolfsson, 2017, p. 21) and enhance productivity (Aghion et al., 2019, p. 254). To fully comprehend AI's potential and the repercussions stemming from its ongoing development, it is crucial to examine both the possible advantages and risks associated with this technology (Yeung, 2019, p. 18).

While AI may indeed displace numerous jobs, it concurrently presents many new employment possibilities (McAfee & Brynjolfsson, 2017, p. 21). The creation and deployment of AI systems necessitate an array of skilled professionals, including data scientists (Krishna et al., 2018, p. 592), software engineers, and AI specialists (Bughin et al., 2017, p. 39). Moreover, the implementation of AI in sectors such as healthcare (Topol, 2018), finance, and transportation (Okrepilov, 2022, p. 233) could result in novel job roles and business models. From an entrepreneur's point of view, AI can boost efficiency and productivity (Aghion, 2019, p. 263). It is capable of improving customer service response times (Frey & Osborne, 2017, p. 20) and enhancing supply chain management effectiveness in logistics (Toorajipour et al., 2020, p. 510).

Additionally, AI systems can help tackle global challenges, such as climate change—a pressing issue identified by the United Nations (United Nations, 2016). AI-driven systems can be employed to optimize energy consumption and decrease greenhouse gas emissions (Hu et al., 2022, p. 1279-1282; Lia & Yao, 2021, p. 778-779). Furthermore, AI can be utilized to monitor and forecast the consequences of climate change, such as predicting disease spread (Santangelo et al., 2023, p. 175) or assessing the risk of natural disasters (Kuglitsch et al., 2022, p. 1579). In the realm of education, AI has the potential to improve educational outcomes by offering personalized learning experiences (Krishna et al., 2018, p. 593) and facilitating the development of innovative educational technologies (Ezzaim et al., 2022, p. 3).

AI holds the potential to generate a multitude of jobs, streamline existing processes, increase productivity, and address global challenges. It is essential to carefully balance the potential benefits and risks of AI in tackling these issues and to ensure its responsible and ethical application (Yeung, 2019, p. 67).

2.4 Disadvantages and Potential Challenges of AI

Turing (1950) discussed the potential future risks and hazards that humanity may face due to the advancement of artificial intelligence. He raised concerns about AI becoming excessively intelligent, potentially exposing threats (Turing, 1950, p. 454-459). Another associated risk is people placing too much trust in AI technology. Weizenbaum (1983, p. 26-27) developed ELIZA, a chatbot simulating a psychotherapist, and argued that despite its perceived complexity, it merely consists of programmed responses and lacks understanding of human emotions or experiences. He consequently warned against overreliance on AI and its responses.

Bostrom's concept of superintelligence refers to an AI system that significantly surpasses human intelligence in areas such as creativity, general knowledge, and social skills (Bostrom, 2014, p. 39-45). This notion aligns with the earlier mentioned technological singularity issue. He suggests, that the focus should be on developing advanced AI in a secure and ethical manner (Bostrom, 2014, p. 291). The prevailing AI development approach overly concentrates on optimizing algorithms (Russel, 2019, p. 11) rather than ensuring machines align with human values (Russel, 2019, p. 68). A key challenge is placing more emphasis on value orientation and safety in AI development, with the objective of having AI comprehend and integrate human values into its behavior (Russel, 2019, p. 62).

While some experts posit that AI will generate new job opportunities (McAfee & Brynjolfsson, 2017, p. 21), others foresee significant job displacement, especially in industries with repetitive and predictable tasks (Bughin et al., 2017, p. 11). As AI algorithms advance (Topol, 2018, p. 50), they may be capable of executing various tasks currently performed by humans (Toews, 2021), leading to job displacement in sectors like manufacturing, data entry, and customer service, characterized by highly repetitive or predictable tasks (Frey & Osborne, 2017, p. 68-73).

The ethical ramifications of AI's influence on the future of work are also crucial (Yeung, 2019, p. 38). It is vital to ensure that AI systems do not discriminate against specific groups (Procon, 2022) and maintain transparency and accountability in their decision-making processes (Kuziemsky, 2016, p. 4-7). Moreover, addressing the potential impact of AI on employment and income distribution is essential to guarantee that AI's benefits are widely shared (Toews, 2021). In the case of extensive job displacement, support for affected workers and addressing income inequality issues will be necessary (Bughin et al., 2017, p. 37). The responsible development and implementation of AI are paramount to ensure that its use benefits society as a whole (Yeung, 2019, p. 41).

2.5 Types and Functions of Artificial Intelligence

As highlighted in earlier chapters, AI exhibits considerable versatility in both the factors contributing to its development and its application areas. It has been hard to find a definition of artificial intelligence that is universally applicable.

Various methods can be employed to categorize AI, with the most prevalent approach focusing on the functionalities of artificial intelligence. AI can be classified into Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Superintelligence (ASI) (Girasa, 2020, p. 10).

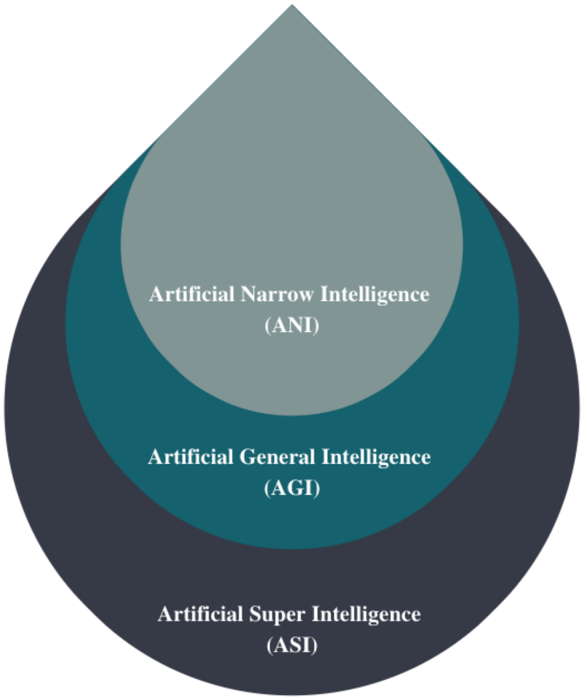

Figure 1 Scope of AI
Adapted from: Girasa (2020, p. 11)

ANI, often referred to as "weak" AI, is characterized by the fact that artificial intelligence only deals with a single task and usually performs it excellently, or better than humans. The examples of Watson, DeepBlue or AlphaGo fall into this category, among others. The word “weak” is used here to narrow down the scope of tasks, as this AI cannot perform other things (Tegmark, 2017, p. 106). AGI, or "strong AI," describes the next level of AI development that attempts to mimic the human brain and is therefore trained not only to perform a specific task but to perform a wide range of tasks. To date, no established AGI has been developed, but a 2020 study identified 72 AGI projects worldwide with active research underway to develop an AGI (Fitzgerald et al., 2020, p. 20). The next most powerful form of AI within this classification is ASI, which is often used in conjunction with technological singularity. The ASI is a form of AI that is more powerful than a human in every way. This would then include this AI having the ability to have emotions as well as relationships. According to Tegmark's (2017, p. 174-175) definition, an AI can be classified as an ASI, or Artificial Superintelligence, if it meets three logical steps. The first step is the creation of a human-level AGI, or Artificial General Intelligence. The second step involves using that AGI to create an artificial superintelligence. Finally, step three involves the use, or rather the unleashing, of that ASI. Therefore, to classify an AI as an ASI, it must first reach the level of human-level AGI, then be used to create an even more advanced intelligence, and finally be unleashed or put to use in some capacity. However, whether achieving an ASI is even possible is questionable and can only be answered in the future.

Another type of classification that is currently used to distinguish current ANI from each other is the classification into the different functions for which these ANI are developed.

The following seven functions can be found in the literature. These are just a few of the functions that a certain AI is trained to perform; likewise, the functions may overlap. Nevertheless, they provide an overview of how versatile AI is being used and what the following chapters on AI research and development refer to.

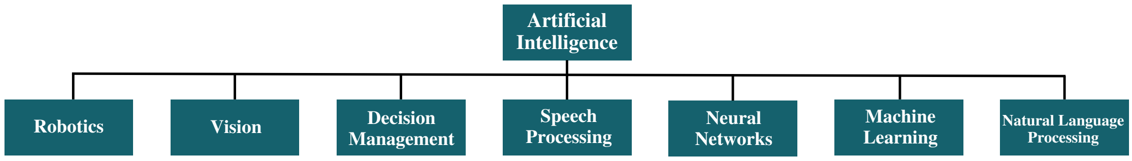

Figure 2 Functions of AI
Adapted from: (Girasa, 2020, p. 13-21; Zhu, 2021, p. 4)

Robotics
Robotics is a swiftly expanding domain of artificial intelligence, encompassing programmable machines capable of executing tasks ranging from straightforward, repetitive actions to intricate problem-solving activities (Brougham & Haar, 2018, p. 239-240). The development and creation of these robots necessitate expertise from various disciplines. These include computer science and artificial intelligence for software development, as well as mechanical and electrical engineering for hardware construction (Vrontis et al., 2022, p. 1251). Typically, robots can function autonomously or with minimal human intervention, operating in environments that may be hazardous or challenging for humans (Vrontis et al., 2022, p. 1252).

Vision
Vision or computer vision is an area of AI that deals with the development of algorithms that enable machines to understand and interpret visual information (Yeung et al., 2018, p. 1271). This can be images, videos, but also other types of visual data (Yeung et al., 2018, p. 1271). The main goal is to enable the machine to identify specific objects in the data. One industry that is taking advantage of this is healthcare, where AI algorithms are used to detect and diagnose diseases in medical imaging (Prijs et al., 2022, p. 912).

Decision management
Another functional area of artificial intelligence, which often finds its application within finance (Zhu, 2021, p. 2), healthcare (Secinaro et al., 2021, p. 1) and logistics (Toorajipour, 2021, p. 508), is decision management. The goal is to optimize and automate decision-making processes in order to make more informed and efficient decisions (Zhu, 2021, p. 2). Decision management also incorporates elements of other functional areas and uses algorithms and models to analyze a set of data to identify patterns and trends and make decisions based on them (Zhu, 2021, p. 4). These can also be designed to adapt and improve over time with additional data. However, decisions regarding human integration and the underlying rule-based systems and algorithms are

something that depends on the specific requirements of the company and the developers (Toorajipour, 2021, p. 511).

Speech Processing

Speech processing entails developing algorithms and techniques that enable machines to comprehend and process human speech (Ran et al., 2021, p. 1). This encompasses speech recognition, which transforms spoken words into text, and speech synthesis, which produces speech from text or other inputs. A major challenge in speech processing is addressing the variability and intricacy of human speech, including variations in accents, pronunciations, and speech patterns, as well as coping with background noise and other disruptions (Ran et al., 2021, p. 2). AI applications of speech processing include virtual assistants like Apple's Siri or Amazon's Alexa, voice-to-text dictation software, and voice-activated controls for smart homes and other devices (Hoy, 2018, p. 82).

Neural Networks

Neural networks represent another form of artificial intelligence, in which AI mimics the function and structure of the human brain, consisting of interconnected artificial neurons or nodes that process and convey information across multiple layers (Puri et al., 2015, p. 3; Wong & Selvi, 1998, p. 129). Neural networks are commonly employed in decision-making processes, such as financial forecasting or fraud detection (Wong & Selvi, 1998, p. 131). A distinguishing feature of neural networks is the training process, during which the AI is provided with a dataset and learns and adjusts based on that data. This process is typically iterative, with the objective of training the AI using data until the desired accuracy level is attained (Wong & Selvi, 1998, p. 134).

Machine Learning

As mentioned in the beginning, there can also be overlaps in these functions. This is the case with neural networks and machine learning, where neural networks can be counted as another subcategory of machine learning, specializing in pattern recognition, and adapted to the structure of a human brain (Russel & Norvig, 2016, p 651; Smith, 2019, p. 47). Machine leaning deals with the development of algorithms and models that enable machines to make certain predictions and decisions based on data. The system is trained with a set of data and the goal is to make predictions about new data (Russel & Norvig, 2016, p 652; Smith, 2019, p. 49). Overall, this artificial intelligence function is used in many industries where data is constantly changing or evolving. As data becomes more extensive and complex, machine learning is likely to remain an important area of research and development in the years to come (Girasa, 2020, p. 14).

Natural Language Processing (NLP)

Natural language processing (NLP) concentrates on enabling machines to comprehend, interpret, and generate human language (Chowdhury, 2003, p. 51). Unlike speech recognition, which primarily deals with recognizing and synthesizing speech, NLP tackles language translation, sentiment analysis, text classification (Chowdhury, 2003, p. 51-56), and chatbot creation (Wong, 2022, p. 3). The emphasis is on grasping the meaning behind natural language data and producing suitable responses (Chowdhury, 2003, p. 51).

2.6 Research and Development on Artificial Intelligence

The field of artificial intelligence is advancing at a rapid pace, with AI research and development taking center stage for many companies and researchers across the globe. Currently valued at $86.9 billion, the AI market is expected to soar to $407 billion by 2027, exhibiting a compound annual growth rate of around 36.2% (MarketsandMarkets, 2022). This growth stems from the escalating adoption of AI technologies in diverse sectors such as healthcare (Secinaro et al., 2021, p. 1), finance (Zhu, 2021, p. 2), retail (Cheng & Jian, 2021, p. 260; Ruan & Mezei, 2022, p. 7), and transportation (Toorajipour, 2021, p. 508). AI research and development is propelled by the rising demand for AI applications that can boost productivity, streamline processes, and confer a competitive advantage (Hilty et al., 2021, p. 61; Zheng et al., 2019, p. 916). Progress in various disciplines (Russel & Norvig, 2016), as well as continuous enhancements in computing power and the ability to process, analyze, and disseminate vast data sets (Russel & Norvig, 2016, p. 652; Smith, 2019, p. 49), have driven the emergence of AI. Furthermore, global AI research and development have benefited from public research funding and policy (Loucks et al., 2019).

Nations are harnessing AI to bolster productivity, competitiveness, and economic expansion (Cath et al., 2018). Additional aims include innovation, technological leadership, and national security; augmenting manufacturing prowess and cultivating smart cities in China (Appelbaum et al., 2018, p. 656-657); and fostering a smart society in Japan (Mashiko, 2020).

The AI boom has been fueled by an influx of venture capital and start-ups, as well as substantial private R&D investments, predominantly by large companies in the U.S. and China (Webb, 2019, p. 4). Due to the expansive, dynamic, and fast-moving nature of the AI domain, it is imperative to devise methods that can outline the scope of the field and trace its research and innovation paths. Gaining insights from mapping and tracking research and innovation is vital for funders, businesses, and other stakeholders (Liu et al., 2021, p. 3155).

There are several ways to assess the current state of global research and development. One common technique is to scrutinize companies' financial investments in R&D. Investigating R&D spending offers insight into the front-runners in this area (European Commission et al., 2022, p. 2). In 2021, the information and communication technology (ICT) industry, which encompasses AI, experienced the highest growth rate worldwide. Closer inspection of the industry shows that R&D investment in ICT services in the USA and China grew by approximately 21%, representing an investment of over 150 billion EUR (European Commission et al., 2022, p. 8).

Private investment in AI in 2021 totaled nearly $93.5 billion, more than double the overall private investment in 2020. The United States led in both total private investment in AI and the number of AI start-ups, with figures three and two times higher, respectively, than China, the next highest country in these categories (Zhang et al., 2022, p. 12). However, financial investment alone does not yield a comprehensive view of the state of R&D in ICT services and AI.

A more research-oriented approach involves incorporating scientific publications, patents, and trademarks to gain a deeper understanding of innovation performance within the field (Brown et al., 1998, p. 33). In recent years, there has been a marked increase in the number of publications, especially in AI-related fields such as pattern recognition (accounting for 27.59% of publications), machine learning (21.31%), and computer vision (13.24%) (Zhang et al., 2022, p. 19). Moreover, the number of AI patents filed in 2021 has risen significantly compared to 2015, with a compound annual growth rate of 76.9%, equivalent to a 30-fold increase (Zhang et al., 2022, p. 36). Upon examination, it becomes evident that there has been a positive trajectory in both financial investments in artificial intelligence and the production of scientific publications, patents, and trademarks.

2.7 Patents and their Utility

Artificial intelligence has emerged as a critical area of research and development within the technology industry, with numerous companies allocating substantial resources toward the development of innovative AI technologies. Consequently, these organizations are confronted with the challenge of protecting their innovations to ensure that they reap the financial benefits associated with their investments (Baudry & Dumont, 2017, p. 40). Similarly, it is imperative for scientists and researchers to validate their discoveries and establish ownership. Patents serve a crucial function in this context.

Functioning as a type of intellectual property, patents afford legal protection to companies, inventors, and creators (Baudry & Dumont, 2017, p. 22). Generally, they defend inventions by granting the patent holder the exclusive right to prevent others from duplicating or employing their inventions without consent (Baudry & Dumont, 2017, p. 14). In exchange for this protection, however, the owner is obligated to publicly disclose their invention's details, thereby fostering research and development within the respective field (Baudry & Dumont, 2017, p. 15-28).

Creators can choose from various patent types, including utility patents, design patents, provisional patents, and plant patents (U.S. Department of Commerce, 2021, p. 15). Utility patents are the most prevalent, covering new and useful machines, processes, compositions of matter, and articles of manufacture. Design patents protect new and original ornamental designs (U.S. Department of Commerce, 2021, p. 75). Provisional patents allow inventors or applicants to establish an early filing date for their invention through a less formal document that briefly describes the creation or invention and sets a priority date. This date is crucial for determining the novelty and non-obviousness of the invention and gives the inventor 12 months to file a regular patent application (U.S. Department of Commerce, 2021, p. 74). During this time, the inventor can label their invention as "patent pending," which can attract investors and potential buyers (Baudry & Dumont, 2017, p. 40). Plant patents concern new and distinct plant varieties (U.S. Department of Commerce, 2021, p. 76).

The patent application process can be intricate and lengthy. It typically involves conducting a patent search to ensure the invention is new and non-obvious compared to existing inventions (Baudry & Dumont, 2017, p. 15-16). The process also includes preparing and submitting a patent application to the relevant Patent and Trademark Office and addressing any objections raised by the examiner.

Upon receiving the patent grant, the owner acquires exclusive rights to utilize, produce, and market their invention for a duration of up to 20 years (Baudry & Dumont, 2017, p. 15-19). Throughout this time frame, the owner possesses the option to license their patent to third parties or initiate legal proceedings in instances of infringement (Baudry & Dumont, 2017, p. 15).

2.8 Innovation, Growth, and the Role of Patents.

Patents are an important part of the innovation and growth theory of companies. In “The Theory of Economic Development”, Schumpeter's (1934) primary work on innovation economics, the author discusses how innovation and entrepreneurship are the main forces behind economic growth and development. He focuses on the function of patents and how they encourage investors and company owners to create new technology and launch new ventures (Schumpeter et al., 1983, p. 191). A few years later, Schumpeter (1942) expands on his theory by introducing the idea of "creative destruction" and describes how innovative businesses achieve economic development by bringing new technology and business models, upsetting established sectors, and thus establishing new ones. The process of "creative destruction" is essential for economic progress, it "incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one" (Schumpeter, 1942, p. 83). The theory was expanded upon to demonstrate that technological change is the driving force behind long-term growth.

The well-known "Solow model" shows that technological progress is one of the biggest influences, besides capital and labor (Solow, 1956). It predicts that economies will converge to a steady-state equilibrium in the long run and that sustainable growth can only be achieved through technological progress (Solow, 1956, p. 71). However, Solow presents technical progress as an exogenous variable and is thus not explicitly explained in the model or rather is determined by factors beyond the control of the model. In further subsequent development in the years of growth theory, factors as technological change and innovation were incorporated as an endogenous variable, which has the implication that they can be actively reinforced by policies and investments (Romer, 1990, p. 72). It shows, when considering the growth of firms, how important innovation is as a driving economic force and that technological change is influenceable by market incentives, investments, and new knowledge. In this context, Arrow (1962) argues that patents can also be seen as promoting innovation because they provide incentives for investors to invest in research and development. Patents represent an attractive method of financial reward for an invention (Arrow, 1962, p. 617). However, patent protection can have disadvantages for consumers, such as the potential for reduced competition and higher prices (Arrow, 1962, p. 617).

For sustained success and growth, a company must be able to innovate and adjust to shifting market conditions (Penrose, 2009, p. 121). This is necessary so that businesses can compete more successfully in dynamic and evolving marketplaces by offering new goods and services that cater to consumers' demands and preferences while attacking the steady-state equilibrium (Penrose, 2009, p. 121–124). Christensen's work on disruptive innovation, within the literature on growth theory and innovation, also highlights the significance of being positioned to first anticipate and then respond to these disruptive innovations (Christensen et al., 2018, p. 1062). Established businesses that take too long to develop or adapt to these changes face the risk of being surpassed by younger, more innovative rivals.

As has been shown, it is vital for companies to be innovative, and it can be beneficial to patent your invention to protect it from others. Companies tend to apply for patents when faced with certain conditions, such as strong competition or the presence of complementary assets (Nelson et al., 2000, p. 28). However, the decision to patent is not always straightforward, and companies must consider factors such as the cost of obtaining and enforcing the patent, as well as the disclosure of proprietary information (Nelson et al., 2000, p. 13). Nevertheless, it is possible to investigate the relationship between patents and innovation. Hall & Ziedonis (2001, p. 29) found a positive relationship between patents and innovation measures, such as R&D expenditures and the number of new products introduced. The authors also note that patents provide benefits beyond the financial rewards, namely the message to investors and customers that the company is committed to innovation and its inventions (Hall & Ziedonis, 2001, p. 14).

Other studies also examined the value of patent rights. The findings suggest that patents filed in multiple countries and those that are subject to opposition proceedings have a higher value, also suggesting that patents can bring significant economic benefits to inventors and companies (Harhoff et al., 2003, p. 1943). However, the value of patents varies by industry and stage of innovation, and patenting is not always the best strategy for every company (Harhoff et al., 2003, p. 1960). In addition, existing literature has shown that information on patent applications is useful to measure the economic value of a technology (Lerner, 1994, p. 322; Narin et al., 1987, p. 150) and patents can serve as an indicator for identifying emerging technologies (Lee et al., 2018, p. 293). Furthermore, research has identified a strong relationship between patents and exports, particularly in the computers and communications technology industry where there is significant patent activity and export volume (Frietsch et al., 2014, p. 550). This finding implies that patents can serve as a useful metric for measuring macroeconomic growth (Frietsch et al., 2014, p. 553-554).

2.9 Theory and Hypothesis Development

In the research on patent applications and total factor productivity, more frequent filing of patents is associated with an increase in innovation (Guo, 2015, p. 602). In addition, companies that regularly file patents are able to protect themselves in financially difficult times (Kumar & Sundarraj, 2016, p. 288). However, obtaining patents can be a costly and time-consuming process, with benefits that may not be immediately reflected in the company's financial performance (Agostini et al., 2015, p. 247-248). Companies are evaluating the effectiveness of the innovation process and seeking better budget control as innovation costs rise (Dunk, 2011). Nevertheless, Patent quantity, which refers to the grouping of connected patents under the management of a company (Huang, 2016, p. 47), may attract market investors because they could increase a company's visibility and exposure (Baudry & Dumont, 2017, p. 40). This is also supported by Hall and Ziedonis (2001, p. 14), who concluded that patents provide non-financial benefits, such as informing customers and investors about a company's commitment to research and its inventions. Furthermore, patents and innovation indicators such as R&D costs and the number of new goods brought to market have been shown to be positively correlated. In addition, research has revealed a strong correlation between patents and exports, especially in the fields of computers and communications technology, where there is significant exportation and patenting activity (Frietsch et al., 2014, p. 550). Thus, patent quantity can be a competitive advantage and economic gain for a company.

These arguments lead the researchers to the following hypothesis:

Hypothesis 1: AI patents owned by companies have a positive effect on company's earnings.

The ability of a company to innovate and develop distinctive products or services that set it apart from its rivals is one of the key aspects that determines its success (Penrose, 2009, p. 121). One approach for businesses to obtain a competitive edge and protect their inventions is through patents (Baudry & Dumont, 2017, p. 14). Yet, not all industries may see the same effects of owned patents on a company's earnings. The degree of technological complexity, market size, and level of competitiveness are only a few of the distinctive traits that are specific to each industry (Porter, 1979, p. 137-145). Hence, patents might be more valuable in industries characterized by high competitiveness and technological complexity, as securing specific inventions could be crucial for gaining a significant competitive advantage.

High-tech industries, like biotechnology and pharmaceuticals, generally require significant investments in research and development (Griliches, 1990, p. 8). These industries may see a stronger link between owned patents and company earnings, as they heavily depend on technological innovation for growth and competitiveness. On the other hand, low-tech industries, such as retail or travel, which are less technologically complex, might have a weaker connection between patents and earnings. To test the assumption that patenting is more profitable in high-tech industries than in low-tech industries, the researchers plan to study the effects of owned AI patents on company earnings. The researchers will particularly focus on comparing the differences between high-tech and low-tech industries. These categories are defined based on their R&D activity intensity and the adoption of cutting-edge technologies (Eurostat, 2020; Hoxha & Kleinknecht, 2020, p. 4). High-tech industries usually have higher R&D spending and a larger number of patent applications than low-tech industries (Archibugi et al., 2009, p. 928-930), which may further support the hypothesis that patenting is more profitable in high-tech industries.

Therefore, the second hypothesis, informed by the existing literature, is as follows:

Hypothesis 2: Patenting contributes more to a company's earnings in high-tech industries than in low-tech industries.

The success of a company often hinges on its ability to innovate and create unique products or services that differentiate it from competitors. Patents can provide businesses with a competitive advantage and protect their inventions. However, the impact of owned patents on a company's earnings may not be uniform across different company sizes.

The concept of "absorptive capacity" (Cohen & Levinthal, 1990) is one theoretical explanation as to why the effect of owned patents on firm earnings may be less pronounced for larger firms. Absorptive capacity is referred to the ability of a firm to identify, assimilate, and apply external knowledge to improve its innovation capabilities (Cohen & Levinthal, 1990, p. 128). Due to their size and resources, large companies have a higher capacity for absorption, which enables them to acquire and incorporate external information more successfully than smaller companies (Cohen & Levinthal, 1990, p. 132). As a result, the value of patents may be less significant for large companies than for smaller companies because large companies can rely on their absorptive capacity to create and exploit new inventions. Empirical studies have also established a link between absorptive capacity and patenting. For instance, Zahra & George (2002, p. 196) provided a review of absorptive capacity and its relationship with patenting activities. Large firms, with their extensive resources and established market positions, may prefer to rely on secrecy in routines and processes as an isolating mechanism to protect their competitive advantage. By keeping their innovations secret, these firms can prevent competitors from accessing vital information that could potentially weaken their market position. Additionally, large firms might possess the resources and capabilities to maintain secrecy more effectively than smaller firms, making this approach a more attractive alternative to patenting (Zara & George, p. 2002, p. 196-197). Moreover, Dziallas & Blind (2019, p. 11) conducted an extensive literature analysis on innovation indicators, including absorptive capacity and patenting, exploring their interplay at various stages of the innovation process. These studies demonstrate that absorptive capacity can influence a firm's patenting activities and the overall innovation process, further reinforcing the idea that the value of patents may be less significant for companies with higher absorptive capacity.

The idea of "diminishing returns" (Samuelson & Nordhaus, 2001, p. 110) is related to a theoretical justification for why the impact of patents on corporate revenues may be less significant for larger firms. According to the concept of diminishing returns, a resource's marginal advantages are said to diminish with time as a company spends more on it (Samuelson & Nordhaus, 2001, p. 110). Larger companies may have a bigger portfolio of patents, which might lessen the marginal value of any individual patent.

These theoretical reasons collectively imply that the impact of owned patents on business earnings may be less pronounced for larger organizations due to their stronger absorptive capacity and larger patent portfolios. An empirical test of this hypothesis can shed light on the variables that affect the relationship between patents and firm earnings, and aid in strategic decision-making for businesses of all sizes.

Hypothesis 3: The effect of owned patents on earnings is less pronounced the larger a company is.

3 Methodology

3.1 Ontology

Unlike the natural sciences, social science, as the name implies, investigates social phenomena. As social phenomena are constructs created by society, according to certain research paradigms, they lack the objectivity of natural science, thus the research in social sciences may be influenced by the researcher's worldview and philosophical background. The research of how reality is perceived is called ontology (Wahyuni, 2012, p. 69). Ontological assumptions thus deal with the question of what constitutes reality (Scotland, 2012, p. 9). Ontological assumptions can be viewed on a spectrum, with the two extremes being positivism and interpretivism (Collis & Hussey, 2013, p. 49). Positivism, originating from the natural sciences, states that reality is external and objective (Wahyuni, 2012, p. 71) and exists independently of the researcher (Scotland, 2012, p. 10). Thus, according to the positivist's ontology, only one reality exists, and everyone experiences the same sense of reality (Collis & Hussey, 2013, p. 47). On the contrary, interpretivists believe that "…reality is constructed by social actors and people's perceptions of it. (Wahyuni, 2012, p. 71)." Therefore, unlike the positivist claim of a single, objective reality, interpretivism states, that each person has their own sense of reality and there are consequently multiple realities (Collis & Hussey, 2013, p. 47).

When researching, the study design must align with the scientists' worldview and philosophical background (Scotland, 2012, p. 9). To reiterate, this thesis aims to investigate how AI patenting effects different companies' business outcomes by statistically analyzing preexisting datasets. A positivist ontological paradigm was chosen for this study as it allows for the investigation of AI patenting effects on business outcomes through the use of objective and measurable data. This study employs secondary, preexisting datasets, and uses statistical methods to analyze said data, consequently, the researchers believe this study to be as objective as possible. By employing statistical methods to analyze preexisting datasets, the researchers aim to establish causal relationships between AI patenting and business outcomes. Additionally, as the analysis of this study is based on observable and measurable data, and by highlighting the source of the data and outlining the methods of analysis used, this study is also replicable and empirical. Lastly, the researchers use a large sample size and various statistical methods to enable the generalizability of their findings. In conclusion, due to the previously mentioned factors and goals of this study and the authors' research philosophy, this thesis follows the ontological standpoint of positivism.

While a positivist approach may not fully capture the complexities of social phenomena, the researchers believe it to be the most appropriate paradigm for investigating the research question. Despite the positivist ontological assumptions, the researchers acknowledge that their own subjectivity and worldview may influence the research process. Therefore, being reflective is an important aspect of this study in order to identify and address potential biases. By being transparent about the methods of data collection and analysis, the researchers attempt to minimize the impact of their own subjectivity on the results.

3.2 Epistemology

Epistemology describes the researcher's view on how to generate, understand, and use the knowledge that is deemed to be acceptable and valid; in other words, epistemology is the theory of knowledge (Marsh & Furlong, 2002, p. 19). It involves examining the relationship between the researcher and that which is researched (Collis & Hussey, 2013, p. 47). Analogous to ontology, epistemological assumptions can also be categorized on a spectrum from positivism to interpretivism. Positivist epistemology states that only observable phenomena can provide credible data and facts (Wahyuni, 2012, p. 70). Thus, positivists aim to maintain an independent and objective stance (Collis & Hussey, 2013, p. 47) and focus on causality and law-like generalizations (Wahyuni, 2012, p. 70). The following analogy visualizes this paradigm well:

"A tree in the forest is a tree, regardless of whether anyone is aware of its existence or not. As an object of that kind, it carries the intrinsic meaning of treeness. When human beings recognize it as a tree, they are simply discovering a meaning that has been lying in wait for them all along. (Crotty, 1998, p. 8)."

Meanwhile, interpretivism postulates that the world does not exist independently of our knowledge of it (Grix, 2004, p. 83), with meaning being subjective and a social phenomenon (Wahyuni, 2012, p. 70). An advantage of the interpretive epistemology is the focus on the details of the situation, the reality behind these details, subjective meanings, and motivating actions (Wahyuni, 2012, p. 70). Continuing the tree analogy:

"We need to remind ourselves here that it is human beings who have constructed it as a tree, given it the name, and attributed to it the associations we make with trees. (Crotty, 1998, p. 8)."

This study, corresponding to the ontological assumptions, uses a positivist epistemology. This implies that in this paper, the researchers collect and analyze data objectively and without bias. Moreover, the aim of this epistemological assumption is to generate results which fulfill the conditions of reliability, validity, and generalizability (Collis & Hussey, 2013, p. 47). Collecting the data objectively and free from bias is not an issue as this research utilizes secondary, preexisting datasets, thus the researchers of this study were not involved in collecting the data. Analyzing the gathered data must also be conducted objectively, without the influence of the researchers' personal opinions or interpretations. A positivist ontology and epistemology go together with methodology that relies on experiments and verifying hypotheses (Guba and Lincoln, 1994, p. 109). This means that the researchers will rely on statistical methods and quantitative analysis to test hypotheses and draw conclusions based on the data.

In summary, the positivist epistemology used in this study emphasizes objectivity, generalizability, and causality, which is reflected in the researchers' data collection and analysis. The use of secondary data ensures objectivity, while statistical analysis and checks on the reliability and validity of the data ensure generalizability and accuracy.

3.3 Axiology

Axiology describes the role of values in the research and the researcher's stance in relation to the subject studied (Wahyuni, 2012, p. 70). It addresses whether scientific research should be value-bound or rather value-free (Collis & Hussey, 2013, p. 48), corresponding to the previously mentioned research paradigms of interpretivism and positivism, respectively. Research in interpretivism is value-bound, as the researcher influences and thus is part of the research (Wahyuni, 2012, p. 70). The scientists following this research paradigm acknowledge, that their influence cannot be separated from their research and therefore be subjective. On the other hand, positivism believes research should be free from the researcher's values and influence (Collis & Hussey, 2013, p. 48). The observed data is independent of the observer, and the researcher maintains an objective stance.

Due to the authors' predisposition and the natural fit between the chosen ontology, epistemology, and axiology, a positivist, objectivist axiology has been chosen for this study. This implies, that the values and preconceptions of the authors will not influence this research and that the researchers maintain an objective, detached stance. While it is difficult for researchers to completely remove their values and preconceptions from their research, especially in social sciences, the authors of this study aim to achieve this by following certain steps.

One such step is to clearly define the research question and expected outcome at the beginning, ensuring the research remains relevant and focused. Using statistical analyses to test for validity and robustness further confirms that the results are reliable. Lastly, the research design and methodology should be clearly defined and replicable, so that other scientists can replicate the research and test its validity. This can help to reduce the influence of personal values and preconceptions on the research outcomes.

3.4 Research Approach

The research approach or logic of research reasoning describes the process of how researchers incorporate theory into their study to arrive at their conclusion. In business research, scientific studies can typically be distinguished between inductive and deductive research (Bryman & Bell, 2011, p. 11). Inductive research aims to move from specific findings through their research to a generally acceptable theory (Collis & Hussey, 2013, p. 7). Thus, inductive reasoning can be referred to as "…moving from the specific to the general (Collis & Hussey, 2013, p. 7)." This type of reasoning is typically used in qualitative and interpretivist research.

Meanwhile, deductive reasoning starts with a general principle or theory and uses specific observations or data to test these principles and come to a logical conclusion. In other words, if the premises are true, the conclusion must also be true. Deductive reasoning is frequently associated with positivism and quantitative research (Bryman & Bell, 2011, p. 21).

The main difference between inductive and deductive reasoning is the direction of the reasoning process. While deductive reasoning proceeds from the general to the specific, inductive logic moves from the specific to the general. Furthermore, deductive reasoning is based on logical certainty, while inductive reasoning is based on probability (Collis & Hussey, 2013, p. 7-8). A third less frequently used approach, called abduction, aims to explain research findings through conjecture and educated guesses (Bamberger, 2018, p. 3). This type of reasoning is used, mostly when findings cannot yet be explained by existing theories, when discovering new phenomena, and to elicit tentative claims (Bamberger, 2018, p. 2). This reasoning process likewise does not fit with the authors' research philosophy and the aim of the study, therefore it will not be considered for this thesis.

The research aims to test hypotheses using statistical methods and as previously outlined, follows a positivistic research paradigm, therefore the researchers use the deductive research process. The deductive research approach is shown in *Figure 3* below.

Figure 3 Deductive Research Process
Adapted from: Bryman & Bell (2011, p. 11)

In combination with the positivist research paradigm, the research can follow this research process in this study. Based on previous theory and literature, research questions, are developed. The scientific literature, mentioned in the previous chapter, led the authors to the following previously mentioned research questions:

1. To what extent do AI patents owned by companies positively influence their earnings?

2. How does the impact of owned patents on firm earnings vary between high-tech and low-tech industries?

3. How does the size of a company moderate the relationship between owned patents and earnings?

By collecting and analyzing data on the number of AI patents of firms and their financial data, the previously stated research questions and hypotheses can be tested through statistical methods, such as regression analyses. Based on the analysis, the researchers can draw conclusions whether the data supports or contradicts their hypotheses. If the analysis reveals a significant correlation between AI patents and financial success, it will provide evidence in support of the research questions.

A deductive research approach is appropriate in this instance, as it enables the researchers to systematically test their hypotheses and draw conclusions based on the analysis. It also allows for the use of statistical methods to investigate the relationship between variables, to quantify said relationship, and to control for other factors that might influence the results.

3.5 Research Method

The primary purpose of this thesis is to investigate the relation between the number of AI patents a company owns and its financial performance. To achieve the purpose of this study set out to answer, it is essential to choose an adequate research method. After a thorough investigation into the available methods, the authors have chosen the analytical research method, also known as the explanatory research, as the most fitting method to conduct this study. Analytical research scrutinizes data and information to identify patterns and identify correlations or causal relations between variables (Sue & Ritter, 2012, p. 2). In this context, the authors will examine the connection between the number of AI patents and a company's financial performance and assess whether this correlation differs between different industry sectors and company sizes. The main aim lies in proving or disproving a correlation between these two variables.

Alternative research methods, such as explorative, descriptive, and predictive research can be useful in different contexts (Collis & Hussey, 2013, p. 4), however, they do not seem as relevant to investigate this research question. Explorative research is mainly utilized, when researchers aim to deepen their understanding of a phenomenon, especially when exploring a new or undiscovered research area (Sue & Ritter, 2012, p. 2). Descriptive research, however, is conducted when the aim of the research lies in characterizing a particular phenomenon or group (Sue & Ritter, 2012, p. 2), while predictive research aims to predict future events by analyzing historic or past events (Collis & Hussey, 2013, p. 5). In contrast to these research methods, analytical research enables the researchers to develop statistical analyses with the aim of identifying causal relationships (Collis & Hussey, 2013, p. 5), which is ideal in investigating this thesis' research goal.

Analytical research provides a statistical framework to analyze data and identify the underlying patterns and interactions between variables (Sue & Ritter, 2012, p. 2). The authors will use various statistical methods, such as the regression- and correlation analysis, to identify the connection between patents and financial performance. Regression analysis is a statistical technique, which allows researchers to identify correlations between two or more variables (Collis & Hussey, 2013, p. 282). This method therefore enables the researchers to evaluate the connection between the variables of interest, developed in this thesis' research question. Additionally, a correlation analysis can show the strength and direction of the associated variables (Collis & Hussey, 2013, p. 270).

Furthermore, analytical research allows researchers to address additional factors that potentially influence the financial performance of a company (Baron & Markman, 2003, p. 54), for example the sector, size of the company and market trends (Omri et al., 2015, p. 1076). It is essential to include these and other variables that could potentially influence our variables of interest, as these external factors may bias our results and thus do not show us the true influence between the variables or even lead to wrong conclusions.

In conclusion, the analytical research method is the most suitable research method to identify and explain the potential correlation between AI patents and financial performance of companies, as this method provides a statistical framework to showcase patterns in the data, correlations between variables, and even causal effects thereof. The authors will use multiple statistical methods to illuminate the connection between AI patents and financial performance. Furthermore, analytical research enables the researchers to include other factors that might influence the financial performance of companies, which is essential to acquire a holistic picture of the interplay between these variables.

3.6 Research Strategy

Qualitative and quantitative research are the two primary research strategies commonly employed in social science research (Rutberg & Bouikidis, 2018, p. 209). The choice between these methods depends on the research question, objective, and the required data for the study (Östlund et al., 2011, p. 370).

Qualitative research focuses on exploring and understanding social phenomena by gathering non-numerical data from sources such as interviews, observations, and case studies (Rutberg & Bouikidis, 2018, p. 209). Its advantages include providing an in-depth analysis of complex issues, yielding rich and detailed information, and collecting data in natural settings (Rynes & Gephart, 2004, p. 455). However, qualitative research has its limitations, such as the inability to generalize results to a larger population due to small and non-representative sample sizes (Collis & Hussey, 2013, p. 54).

In contrast, quantitative research emphasizes the use of numerical data and statistical analysis to uncover relationships between variables (Rutberg & Bouikidis, 2018, p. 209). It offers advantages like precise and objective data analysis, hypothesis testing, and generalizability to larger populations (O'Gorman & MacIntosh, 2015, p. 155). Nonetheless, quantitative research may oversimplify complex phenomena and overlook important aspects and details (Bryman & Bell, 2011, p. 619).

For this thesis paper, which explores the relationship between patents and firm earnings, while taking into account various factors (industry, size), quantitative research is a more suitable approach than qualitative research. Quantitative research enables the collection of numerical data that can be analyzed using statistical techniques to identify patterns or relationships between variables (Rutberg & Bouikidis, 2018, p. 209). Researchers can examine data on the number of AI patents filed by companies and their financial information, and employ statistical methods like regression analysis and correlation analysis to investigate the relationship between these variables.

Moreover, quantitative research allows for the generalizability of results to a larger population when using representative data (Bryman & Bell, 2011, p. 163-164). In this study, this could lead to applicable conclusions for numerous companies regarding the profitability and viability of AI technology R&D. Significant trends and patterns can be identified, and variables can be analyzed objectively and thoroughly. Additionally, a positivist research paradigm supports the use of a quantitative research strategy (Guba & Lincoln, 1994, p. 109).

In summary, although qualitative and quantitative research each have their respective strengths and weaknesses, quantitative research is more appropriate for investigating the potential correlation between AI patents and companies' financial success. Quantitative research facilitates the collection of numerical data that can be statistically analyzed to identify patterns or relationships between variables, and enables the generalization of findings to a broader population. *Figure 4* provides a summary of the chosen research paradigm and research assumptions for this research project.

Figure 4 Overview of Methodology

3.7 Ethical Considerations

Ethical considerations are of vital importance to any research, as the researcher's values provide the foundation of the study's code of conduct and thus shapes every step of the research process (Collis & Hussey, 2014, p. 30). Furthermore, research ethics is important for maintaining the scientific integrity of research, upholding human rights and dignity, and fostering collaboration between science and society (Bhandari, 2022). These considerations typically regard the safety and consent of the research participants. Various ethical aspects need to be considered when conducting a study, depending on the type of study. The most significant ethical principles which researchers must consider are privacy, anonymity, accuracy of findings, honesty, and transparency.

Researchers have a moral responsibility, when undertaking research. Without considering ethical principles, scientific research will not be viewed as trustworthy and unbiased and lose its respect, with growing distrust towards science already seen today (Simpson & Rios, 2019, p. 742). Thus, it is important to contemplate and lay-open one's moral principles early in the research process. Ghauri & Grönhaug (2010, p. 22) argue, that honest and objective reporting on a study's findings is the most important ethical aspect, consequently presenting false or misleading results is deeply unethical and immoral.

The paper by Bell and Bryman (2007) has compiled the most common ethical guidelines in business research. As this study uses preexisting, secondary datasets, and does not collect any primary data, some ethical questions are more relevant than others. As previously explained, this study does not gather primary data, hence, ethical considerations regarding respondents' rights, i.e., preventing harm to participants, informed consent, dignity, confidentiality, deception., are not applicable in this context (Bell & Bryman, 2007, p. 72). Other ethical principles, however, are applicable to this research. Affiliation, meaning "the need to declare any professional or personal [associations] that may have influenced the research, including conflicts of interest and sponsorship, and information about the source of the research funding (Collis & Hussey, 2014, p. 32)" is one such principle which needs to be openly mentioned. This research thesis has no affiliation or ulterior motive regarding anything mentioned in this study to report. Accuracy, transparency, and objectivity have been considered in every part of this study. These principles have partially been discussed with the researchers' methodology and ontology. To further provide transparency, the following chapters will examine and critically evaluate the practical methods used over the course of this research. Additionally, to avoid "misleading, misunderstanding, misrepresenting, or falsely reporting the research findings (Collis & Hussey, 2014, p. 32)", this study meticulously presents the sources, methods, procedures, and instruments used to the reader, enabling the reader to come to their own conclusion or validate the researchers' findings, in line with the recommendation by Ghauri & Grönhaug (2010, p. 23). To the authors' best knowledge, the results and the research procedures could not imply conflict, harm, or negative implications for any involved party or reader.

It should also be kept in mind that ethical considerations should be an ongoing process throughout the research project. Therefore, the researchers will reflect on and reevaluate their ethical principles and practices as the research progresses or new information arises.

Umeå School of Business, Economics & Statistic's ethical guidelines and code of conduct has also been considered and reflected upon throughout the research process.

3.8 Literature Search & Source Criticism

When conducting a quantitative study that relies on secondary sources, it is crucial to systematically select reliable sources to ensure the quality of the gathered data. Gill and Johnson (2002) emphasized the importance of thoroughly analyzing the data to assess its limitations and contribution to the thesis. Furthermore, research should build upon previous studies in an objective manner, making sure not to misrepresent it. Thus, a review of the scientific literature can be a valuable tool throughout the research process as it helps identify problems, refine the topic, and develop hypotheses (Nenty, 2009, p. 25).

For this study, the authors used a variety of sources from reputable databases such as Umeå University Library, DiVa portal, EBSCO (Business Source Premier), and Google Scholar. Some of the sources were found during previous courses taken at Umeå University and provided a starting point to begin the research from. It was imperative to the researchers, that the articles and journals used in the study were of high quality, therefore the authors made sure to use peer-reviewed articles as much as possible, as these have a higher status and credibility due to being reviewed by experts in their respective fields (Umeå University, 2022). Identifying peer-reviewed articles was done through Umeå University Library's online search tool, which makes this process very simple and straightforward. Through this process, the researchers were able to gather a significant amount of knowledge on the topic. Additionally, research papers and previous master theses were drawn upon for finding additional sources and inspiring the methodology and outline of this study.

To further assess the reliability of the secondary data sources, the researchers used four main criteria established by Scott (1990, p. 6, cited in: Bryman & Bell, 2011, p. 545): authenticity, credibility, representativeness, and meaning. To ensure authenticity, referring to whether the evidence is undisputable and the source unquestionable, the authors verified the data's source and ensured that it was free from doubt. The credibility of the data, checking for errors or distortions of information, was also assessed. Representativeness was evaluated by considering whether the evidence was typical or atypical. Finally, the researchers assessed the meaning of the data by ensuring that it was clear and intelligible.

In addition to these criteria, especially if the source was not peer-reviewed, the authors also considered the publication date of the sources and examined the authors' reputations and citation records. The publication date can be of interest, as the relevancy of research can quickly diminish, if new research refutes previous findings and assumptions. The number of citations was used to assess a source's quality if it was not peer-reviewed.

Overall, by using a systematic approach to selecting and assessing secondary sources, the researchers are able to enhance their research with reliable, relevant, and meaningful data.

3.9 Topic Selection & Preconceptions

The decision to investigate the relationship between patents and a company's financial outcome was influenced by several factors, as outlined in earlier chapters. Firstly, AI's growing significance in the contemporary economy and its potential to propel business growth. Secondly, there is a scarcity of research on this subject, particularly concerning the impact of AI investments on financial success. Lastly, the researchers possess a personal interest in the field of AI and its potential to revolutionize businesses, industries, and daily life.

Nonetheless, it is crucial to recognize the preconceptions and potential biases that may impact the research process and results. First, the researchers, though interested and relatively informed on the subject of AI, lack a background in computer science or AI development. This may result in a tendency to underestimate the intricacies and challenges associated with widespread artificial intelligence implementation. This bias must be carefully managed to avoid oversimplifying the intricate relationship between investment in AI and financial success.

The researchers acknowledge the possibility of being influenced by the 'hype' and excessive optimism surrounding AI's transformative potential. AI has frequently been discussed in the authors' higher education, often portrayed as a solution to all problems without critically evaluating the technology's strengths and weaknesses or comprehending it beyond a superficial level. Consequently, the research will be approached with a critical and objective viewpoint, considering both the opportunities and limitations of AI and their impact on businesses' financial performance.

Furthermore, the researchers recognize the significance of data quality in ensuring accurate findings. As such, the data chosen from the datasets will be meticulously and impartially selected, and the employed methods will be detailed to expose any potential actions leading to biased outcomes. Other limitations and biases in the research process include possible errors in the data, the chance of omitted variables affecting the results, and the potential for researcher bias. To address these limitations, the researchers will utilize a large sample size, employ multiple statistical techniques, and conduct sensitivity analyses to assess the robustness of the findings. The researchers will also maintain transparency regarding data sources and analytical methods used in the study. In doing so, the researchers aim to guarantee the reliability and validity of the study's conclusions.

In summary, the choice of researching the relationship between patents and a company's financial outcome is based on several factors, including AI's importance in today's economy, the limited research available, and personal interest. However, the researchers are aware of the potential influence of preconceptions and biases on the research process and outcomes, and they will approach the research with a critical and objective perspective, using rigorous data collection and analysis methods to ensure accurate results.

4 Research Method

4.1 Data Sources

This research is based on two databases that were merged in the course of the work. The exact description of the merging process is described in detail in a later part of the paper, which contributes to the reproducibility of this work and our results.

The service of the German Patent and Trademark Office (DPMA) was used for patent data collection. The researchers use German patent data for both German and non-German companies. Although this German data might imply a bias in favor of German companies compared to non-German companies, the DPMA website points out that the DPMA's patent database DEPATIS contains data on publicly available patents and the most important documents of other patent offices and organizations worldwide (DPMA, 2023). Thereby providing a patent database that uses patent data within Europe. Furthermore, to ensure a certain level of consistency, reliability and comparability, it is necessary to choose a single patent system instead of multiple patent systems in different countries (Ahuja & Katila, 2001, p. 205).

In order to relate to the chosen field of artificial intelligence, the researchers limited the patent database in terms of the International Patent Classification (IPC) that fall into the AI category. Fujii & Managi (2017, p. 17) identify patents mainly as AI-related if they are classified under IPC code “G06N”, i.e., “computer systems based on specific computational models (World Intellectual Property Organization, 2019).” Cockburn et al. (2018, p. 16-18) expand this scope to include the category “Robots” and add a keyword search for patent titles. For this work, the researchers decided to use a system recommended by the Organization for Economic Co-operation and Development (OECD) to measure AI-related science and technology developments (Baruffaldi et al., 2020, p. 51). Namely, the inclusion of the IPC codes listed below.

Table 1 IPC Patent Numbers for AI Technology

G06N3	G06N5	G06N20	G06F15/18
G06T1/40	G16C20/70	G16B40/20	G16B40/30

Based on these IPC codes, the DEPATIS database was limited to patents that fall within the classification of AI.

When classifying patents in the field of AI, the researcher observed that the publication and granting of patents has increased exponentially since 2016 (see *Figure 5)*. There is a trend that shows that patents related to artificial intelligence are increasing sharply. However, to develop a holistic view and acquire more observations, the investigators have limited the study to the period between 2010 and 2022.

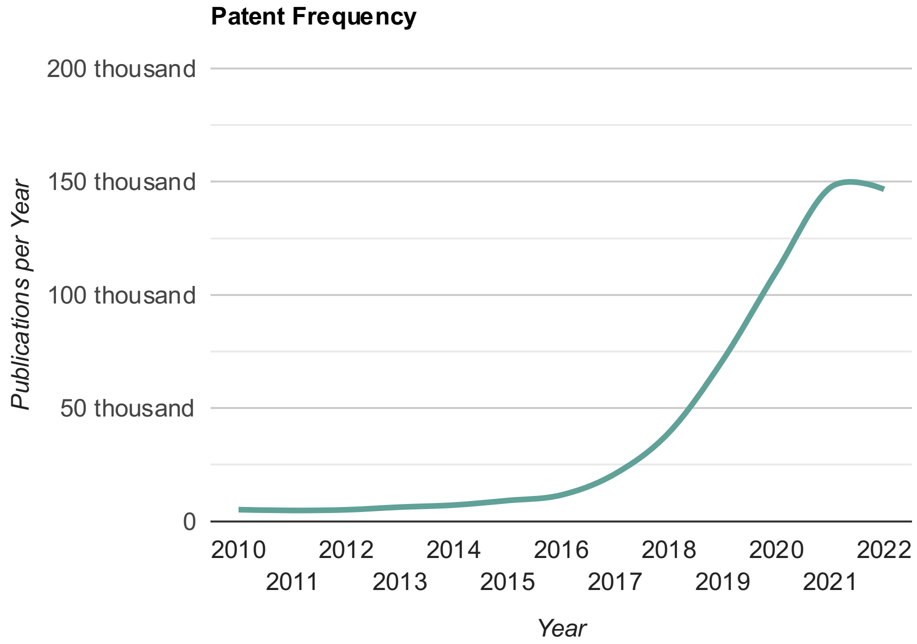

Figure 5 AI Patent Frequency
Source: European Patent Office, 2022

Another restriction of the work relates to geography limitation: the study covers patents and companies that have filed their patents within Europe. This is based on a relatively short time frame in which the study must be completed, so the restriction to Europe was a matter of manageability for the investigators and with the goal in mind of completing the study in the allotted time. Finally, available resources, such as databases, were also a reason for the European focus. However, the researchers argue that by limiting the study to the European region, detailed and reliable data can be collected, in part due to the common regulations and laws in the region (European Patent Office, 2022).

For the obtainment of the company's financial data, the database Orbis Europe was utilized. Orbis Europe is Bureau van Dijk's corporate database, which contains financial information and comparable data sources on private and listed companies all over the world. Bureau van Dijk is a Moody's Analytics company and specializes in enterprise data combined with enterprise search and analysis software (Bureau van Dijk, 2020). To obtain a usable data set, the financial data set must be merged with that of the patents. This procedure is described in a later chapter.

4.2 Construction of Variables

4.2.1 Dependent Variable

EBIT, or Earnings Before Interest and Taxes, is a financial metric that measures a company's operating performance. It describes earnings before considering interest and tax expenses, thus representing the profit generated from core business operations. (Capkun et al., 2009, p. 796). It is calculated by subtracting a company's operating expenses from its revenue before interest and taxes are deducted (U.S. Securities and Exchange Commission, 2021). EBIT is a widely used measure that enables comparisons of companies' operating performances (Eng & Vichitsarawong, 2022, p. 4). It represents the profit generated by a company through its core business operations, without considering the effects of financial decisions and tax obligations. In this study, EBIT is selected as the measure of firm performance, as it aligns with previous research (Strouhal et al., 2018, p. 146) and facilitates the comparison of companies operating in different countries and of various sizes, both factors that can influence corporate taxes and interest rates (OECD, 2022).

Moreover, EBIT is also a key measure used by companies themselves to evaluate their financial performance (Capkun et al., 2009, p. 796; Eng & Vichitsarawong, 2022, p. 4), making it a relevant and meaningful measure to investigate in the context of this study. The use of EBIT as the dependent variable ensures that the analysis is grounded in a well-established and widely used financial metric.

Overall, the choice of EBIT as the dependent variable in this study is well-supported by existing research and is a meaningful and relevant measure for assessing the relationship between independent variables and company financial performance (Capkun et al., 2009, p. 796).

4.2.2 Independent Variable

The researchers chose to use patents as an independent variable, more specifically, patents granted. Patents are often used as a measure of companies' innovation efforts as well as intellectual property portfolio and growth potential (Baudry & Dumont, 2017, p. 40; Hall et al., 2005; Teece, 1986, p. 304). However, when analyzing the relationship between patents and company performance, e.g., EBIT, it is important to carefully decide which type of patents to include in the analysis.

In general, granted patents are considered to be of higher value than patent applications (Hall et al., 2005; Harhoff et al., 2003, p. 1360). This is because granted patents offer greater legal certainty. The reason for this is that granted patents have already been examined and thus the requirements for patentability are deemed to have been met (Lanjouw & Schankerman, 1997, p. 24-25). Granted patents thus offer greater certainty that the company’s innovation efforts have been recognized and confirmed by a third-party authority.

Furthermore, granted patents tend to have a higher quality than patent applications. This is partly because the process from application to grant is often lengthy and complex, and not all patents are ultimately granted (Harhoff et al., 2003, p. 1360). Similarly, companies frequently file patent applications for strategic reasons, such as to deter competition, rather than to develop and implement real innovation (Gurgula, 2020, p. 1068). A study by Kogan et al. (2017, p. 674) found that the stock market reacts more positively to the granting of patents than to the filing of patents. This suggests that granted patents are a more reliable indicator for the company's future growth potential.

Another reason why patents granted are used as an independent variable in this study is the significant time lag that can occur between the filing of a patent application and the granting of the patent (USPTO, 2023). The European Patent Office (EPO) states that the grant procedure takes about three to five years from the date of filing (EPO, 2023). This time lag could distort the relationship between patents and financial performance measures because filing a patent does not necessarily mean that the innovation has been completed or implemented. Thus, including patent applications in the analysis could introduce a significant time lag. While there may also be a time lag between the granted patent and EBIT (Abrams et al., 2013, p. 97-98), this will be considered and further discussed in the following chapters.

Additionally, this research uses the natural logarithm of patents instead of the raw number to better capture the non-linear relationship between AI patents and company earnings. This approach addresses potential heteroskedasticity (Wooldridge, 2016, p. 267) and scale disparities across companies, enhancing the robustness of this study's findings. Importantly, the logarithmic patent variable provided more significant regression results compared to the non-logarithmic variable, further justifying its use. Employing the natural logarithm of patents is a common practice in business research (Griliches, 1990), facilitating a more rigorous and reliable analysis.

Over the course of this study, the researchers frequently use the term patents. This term refers to the natural logarithm of granted patents in the field of artificial intelligence, following the previously mentioned IPC-code classification.

4.2.3 Control Variable

In research studies, control variables are used to help isolate the effect of the independent variable of interest on the dependent variable, while holding constant other factors that may affect the relationship between them. One such control variable that the researchers chose is total assets. The fixed effects model, used in later stages of this paper's analysis, further parcels out stable variables, such as country effects.

Total assets, which describes the total value of a company's assets, encompasses both tangible assets like real estate, machinery, and equipment as well as intangible assets like goodwill, patents, and trademarks (Stickney, 2011, p. 15). The researchers assume that companies with larger total assets have economies of scale that enable them to reduce their production costs, which can increase their profitability and thus their EBIT. Furthermore, there might be undesirable correlations as patents are included as intangible assets within the total assets.

Another control variable considered in this study is long-term debt. Long-term debt is a sort of debt that a business can have and is expected to pay back over a longer length of time than a year (Titman et al., 2018, p. 82). Companies frequently utilize it to finance significant capital investments, such as new machinery or buildings, as well as other long-term initiatives. Loans, bonds, and other instruments with maturities of longer than a year are some examples of long-term debt (Titman et al., 2018, p. 703). On the one hand, a company with a manageable level of long-term debt can invest in projects that generate higher returns, leading to an increase in EBIT (Brealey et al., 2017, p. 452). Conversely, excessive long-term debt can lead to higher interest expenses, reducing the company's EBIT (Moyer et al., 2018, p. 430). Additionally, if a company's debt becomes unmanageable, it may need to divert resources away from growth and innovation initiatives to service its debt, further impacting EBIT negatively (Bhattacharya et al., 2017, p. 1889).

One additional relevant control variable is profit margin, which is a financial ratio that assesses a company's profitability by determining the percentage of revenue that is left over after subtracting all expenditures, including operating expenses and taxes. The ratio is calculated by dividing net profit by total revenue (Harrison et al., 2019, p. 479). It displays the portion of revenue that a business keeps as profit after all costs have been paid. The researchers assume that profit margin correlates with EBIT, as profit margin is also closely linked to a company's financial performance. Furthermore, higher profit margins could be used to finance and improve EBIT-related activities and figures.

Furthermore, the researchers assume that a company's employees count may have an impact on both patents and profitability. The number of employees is a proxy for a company's human capital (Becker, 1964, p. 5) and might reflect the company's potential for innovation and its capacity to efficiently utilize its patents. A corporation may have greater resources and experience to innovate and create new patents if it has a larger workforce. A company's workforce may influence its operational costs and expenses, which can have an impact on its profitability (EBIT) as they are used in the calculation (U.S. Securities and Exchange Commission, 2021). For instance, a business with a larger workforce may have greater benefits and labor expenditures, which might lower the EBIT.

The next selected control variable is operating revenue, which refers to the amount of money a company generates from its main business. Revenue from the sale of one-time investments or products/services that are not defined as the main business are not included in the calculation (Tuovila, 2020). The researchers assume that operating revenue has an influence on EBIT, since a company's sales directly affect its financial performance. A higher operating revenue may indicate that the company is growing successfully, and this may lead to a higher profitability.

The last variable that the researchers use as a control variable for the analysis is the age of the companies. There is disagreement in the literature whether the relationship between the age of a company and its profitability is positive or negative (Hopenhayn, 1992, p. 1141; Rahman & Yilun, 2021, p. 113). Some studies also show that the relationship changes with the lifecycle of a firm (Akben-Selcuk, 2016, p. 6; Warusawitharana, 2018, p. 21). For the researchers, however, it is important that this relationship exists, which results in this study using the age of the company as a control variable.

4.2.4 Lagging of Variables

In the context of this study, lagging variables is a crucial step in the regression analyses to account for the time it takes for the effects of independent and control variables to impact the dependent variable, EBIT (Baltagi, 2008, p. 167-169). This chapter will provide a comprehensive discussion on the rationale behind lagging variables, the appropriate lag length, and the potential implications of the chosen lag structure for the regression model.

The primary reason for lagging variables in this study is to account for the time it takes for the impact of granted AI patents on a company's EBIT to materialize (Ahuja & Katila, 2001, p. 205). The researchers assume that the benefits of patents, such as competitive advantages and increased revenue from new products or services, take time to manifest (Pakes & Griliches, 1984, p. 18-20). Hagedoorn & Cloodt (2003), in their analysis of measuring firm performance using multiple indicators, found that "The results for the analyses with different time lags turned out to be almost identical with no significant differences (Hagedoorn & Cloodt, 2003, p. 1372)." However, by incorporating a one-year lag for patents, the researchers believe to allow for the time required to integrate the patented technology into the company's operations and generate revenue from the innovations.

Another important reason for lagging variables is to mitigate potential endogeneity issues and simultaneity bias (Cameron & Trivedi, 2005, p. 96). The control variables, such as total assets, long-term debt, profit margin, employees, operating revenue, and the age of the company, may be correlated with EBIT within the same year. By lagging these variables by one year, the researchers believe to ensure that the regression model captures the influence of the control variables on EBIT from the previous year, reducing the likelihood of reverse causality or simultaneity bias in the estimates.

In this study, the researchers have chosen a one-year lag for both the independent variable (number of patents granted) and the control variables. This choice is based on the assumption that it takes approximately one year for the impact of the variables on EBIT to materialize. However, it is essential to acknowledge that the choice of lag length may influence the regression results.

By incorporating a one-year lag for the independent and control variables, this study aims to provide a more robust analysis of the relationship between AI patents and company EBIT. The lagged variables help address potential time lags in effects and mitigate endogeneity issues, improving the reliability and validity of the regression estimates.

The choice of lag length is inherently subjective and may vary depending on the context of the study. While this research employs a one-year lag based on specific assumptions, other lag lengths could be argued for and may find differing results.

In conclusion, lagging variables is a critical step in this regression analysis to account for the time it takes for the effects of the independent and control variables to impact EBIT, as well as to address potential endogeneity issues. The chosen lag structure has implications for the robustness of the regression estimates and the interpretation of the results, highlighting the importance of careful consideration of the appropriate lag length in the study.

4.3 Data preprocessing

4.3.1 Data merging

To perform the analysis, the researchers need to merge the patent database with the database containing the financial data. This is done with Excel. The company and accounting data are merged based on their company name and year. To implement the data on patents, the researchers create a data frame that summarizes the number of patents that each company filed in each year of the relevant period. This data frame is then merged with the accounting and company information based on company name and fiscal year. From the patent database and taking into account the mentioned restriction in section 4.1, the researchers arrive at 432 companies that have filed patents in the time period and under the mentioned IPC classes. Among these companies, 370 are also included in the Orbis Europe database. Importantly, all included companies filed at least one patent during the sample period, ensuring that the analysis captures a comprehensive picture of the relationship between AI patents and EBIT.

4.3.2 Data cleaning

Certain inconsistencies and unrealistic observations exist in the accounting data from the Orbis Europe database, and not all companies in the database are relevant or applicable to this research. To ensure accuracy, it’s important to establish conditions for the observations and companies included in this analysis. Companies must have at least one disclosure regarding their financial aspects within the Orbis database during the 12-year sample period. If they do not provide any indication, they have no impact on the analysis and are therefore redundant. For the most part, this applies to some universities as well as individuals. After merging the data and removing data points that do not meet the criteria mentioned above, the database is transferred from Excel to Stata Ver. 17. However, to perform an analysis of the data, Stata requires the data type must first be formatted from a wide format to a long format, in order to interpret the data as panel data. After removing the data entries that do not meet the specified conditions, marking empty fields as missing values, and formatting the dataset, our final data sample consists of 4407 observations, 339 companies, and 1804 patents.

4.3.3 Outliers

In our analysis, we encountered some outliers in the EBIT and Age variables, which could potentially distort the results of our regression models. To mitigate the influence of these extreme values, we applied the winsorizing technique at the 99 percent level. Winsorizing involves replacing the observations larger than the 99th percentile with the value at the 99th percentile and replacing the observations smaller than the 1st percentile with the value at the 1st percentile (Dixon, 1960, p. 385-388). This approach retains the structure of the dataset while reducing the impact of extreme values on the analysis.

We chose to winsorize the data rather than trimming it, as we believe the observed growth in the outliers is, to some extent, valid. However, if not winsorized, these observations could have an unreasonably large influence on our results. Winsorizing is a widely accepted statistical method for addressing outliers and reducing their impact on analysis, without completely discarding them (Tukey, 1962, p. 18-19; Wilcox, 2012, p. 59).

By employing the winsorizing technique, we have maintained the integrity of our dataset while minimizing the potential bias introduced by extreme values. This approach is supported by existing literature and is considered statistically appropriate when dealing with outliers (Wilcox, 2012, p. 123).

4.4 Construction of Subsets

4.4.1 Industry classifications

To eventually investigate the second hypothesis, we categorize the companies into two industries. **Table 2** presents the distribution of industries in terms of patent ownership and their classification as high-tech or low-tech industries. This categorization of industries is determined by their level of R&D engagement and the implementation of advanced technologies, as outlined by Eurostat (2018) and Hoxha & Kleinknecht (2020, p. 4). The largest industries in terms of patent ownership are Industrial, Electric, Electronic Machinery (20.58%), Computer Software (19.63%), and Business Services (14.74%). However, it is interesting to note that Business Services, despite having a substantial number of patents, is not classified as a high-tech industry.

High-tech industries are represented across various sectors, such as Media & Broadcasting, Computer Hardware, Chemicals, Petroleum, Rubber & Plastic, Communications, Transport Manufacturing, Biotechnology and Life Sciences, and Computer Software. In general, high-tech industries tend to have a higher number of patents compared to low-tech industries.

On the other hand, some industries have a very small representation in terms of patent ownership, such as Leather, Stone, Clay & Glass products, Media & Broadcasting, and Retail, each with only 1 patent. Additionally, there are 14 patents that did not have an industry assigned.

Table 2 Distribution of Industries

Industries	# of Patents	Percent	Companies	High-Tech[1]
Leather, Stone, Clay & Glass products	1	0.06	1	
Media & Broadcasting	1	0.06	1	*
Retail	1	0.06	1	
Agriculture, Horticulture & Livestock	2	0.11	1	
Mining & Extraction	2	0.11	1	
Travel, Personal & Leisure	2	0.11	2	
Property Services	3	0.17	2	
Utilities	4	0.22	1	
Banking, Insurance & Financial Services	6	0.33	3	
Food & Tobacco Manufacturing	6	0.33	3	
Metals & Metal Products	11	0.61	5	
Wholesale	24	1.33	9	
Public Administration, Education, Health, Social Services	33	1.84	10	
Computer Hardware	35	1.95	2	*
Chemicals, Petroleum, Rubber & Plastic	78	4.34	18	*
Communications	151	8.40	11	*
Transport Manufacturing	183	10.18	12	*
Biotechnology and Life Sciences	253	14.07	35	*
Business Services	265	14.74	97	
Computer Software	353	19.63	67	*
Industrial, Electric & Electronic Machinery	370	20.58	49	*
.	14	0.78	8	
Total	1798	100.00	339	

4.4.2 Size classifications

In order to ultimately explore the third hypothesis, we sort the companies according to their size. They are divided into four distinct categories: small, medium, large, and very large, as well as a 'Missing' category for companies with incomplete information. The classification for each company is determined by its size in the final year it appears in the dataset. The criteria for each size category are derived from the classifications established by the Orbis Global Database, provided by Bureau van Dijk (Orbis, n.d.).

[1] high-tech industries indicated by *, classification from European Commission (2018)

Companies in Orbis Europe are deemed very large if they meet at least one of the following criteria:

• Operating revenue of 100 million EUR (130 million USD) or more.

• Total assets of 200 million EUR (260 million USD) or more.

• A workforce of 1,000 employees or more.

• Listed on a stock exchange.

A company is classified as "large" if it meets at least one of the following criteria:

• Operating revenue of 10 million EUR or more.

• Total assets of 20 million EUR or more.

• A workforce of 150 employees or more.

A company is considered "medium" if it satisfies at least one of these conditions:

• Operating revenue of 1 million EUR or more.

• Total assets of 2 million EUR or more.

• A minimum of 15 employees.

If the company is not included within one of the mentioned categories but has available information, it will be classified as "small".

The distribution of company size in **Table 3** shows that small companies account for 11.62% of the total number of patents (209 patents) and are represented by 73 companies in our dataset. Medium-sized companies hold 5.90% of the total patents (106 patents) and are represented by 62 companies. Large companies account for 10.18% of the total patents (183 patents) and are represented by 47 companies. Very Large companies make up the majority of the dataset, holding 71.91% of the total patents (1293 patents) and are represented by 155 companies. The 'Missing' category accounts for 0.39% of the total patents (7 patents) and includes 2 companies with incomplete information. The total number of patents in our dataset is 1,798, with 339 companies being analyzed.

The descriptive statistics presented below provide an overview of the distribution of company size and their corresponding patent holdings within our dataset, which will serve as a foundation for further analysis.

Table 3 Distribution of Company Size

Size classification	# of Patents	Percent	# of Companies
Small company	209	11.62	73
Medium sized company	106	5.90	62
Large company	183	10.18	47
Very large company	1293	71.91	155
.	7	0.39	2
Total	1798	100.00	339

4.5 Descriptive Statistics

In this study, the researchers examine the relationship between AI patents and companies' EBIT, along with other financial variables such as Total Assets, Long-term Debt, Profit Margin, Operating Revenue, Employees, and Age of Company. The provided correlation matrix (**see Table 4**) shows the pairwise correlations between these variables, with an asterisk (*) indicating statistical significance at the $p<.05$ level.

The correlation matrix indicates that *EBIT* (Earnings Before Interest and Taxes) has a statistically significant positive correlation with *Patents* (r = 0.121*), suggesting that companies with more AI patents tend to have higher earnings. However, this correlation does not indicate causation and should be interpreted with caution. Additionally, as the correlation between the two variables is not that strong, the problem of multicollinearity will not be a significant issue in the regression model.

Total Assets and *Long-term Debt* are strongly positively correlated (r = 0.928*), implying that companies with larger asset bases typically have higher long-term debt levels. This relationship makes intuitive sense, as larger companies may have more significant financing needs and are more likely to have accumulated long-term debt.

Operating Revenue and *Employees* show a strong positive correlation (r = 0.865*), suggesting that larger workforces tend to generate higher revenues. This result is consistent with the idea that companies with more employees have a greater capacity to produce goods and services, leading to increased revenue generation.

The *Age of Company* variable demonstrates a moderate positive correlation with *EBIT* (r = 0.408*) and Patents (r = 0.294*), indicating that older companies tend to have higher earnings and more AI patents. This finding could be attributed to the fact that older companies may have had more time and resources to invest in R&D and patent applications.

Lastly, *Profit Margin* has a weak positive correlation with EBIT (r = 0.172*) and a weak negative correlation with Patents (r = -0.019). While the latter relationship is not statistically significant, it suggests that the impact of AI patents on earnings might not be driven solely by increased profitability.

In conclusion, the correlation matrix offers valuable insights into the relationships among the variables in the dataset. Although these correlations do not establish causation, they provide a starting point for further investigation using more advanced statistical techniques such as regression analysis. The relationships between various financial metrics can also be explored in more depth to better understand the complex interplay of factors affecting companies' *EBIT*.

Table 4 Correlation of Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) *ebit*	1.000							
(2) patent	0.121*	1.000						
	(0.040)							
(3) total assets	0.793*	0.115*	1.000					
	(0.000)	(0.036)						
(4) long-term debt	0.751*	0.098	0.928*	1.000				
	(0.000)	(0.138)	(0.000)					
(5) profit margin	0.172*	-0.019	0.096*	0.033	1.000			
	(0.000)	(0.762)	(0.000)	(0.285)				
(6) employees	0.731*	0.242*	0.720*	0.652*	0.082*	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)			
(7) turnover	0.813*	0.149*	0.841*	0.829*	0.061*	0.865*	1.000	
	(0.000)	(0.011)	(0.000)	(0.000)	(0.019)	(0.000)		
(8) *age*	0.408*	0.294*	0.360*	0.248*	0.169*	0.378*	0.400*	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

p-values are in parentheses
* shows significance at p<.05

Table 5 exhibits descriptive statistics for relevant variables in the full sample. The dataset includes 3753 observations from 339 companies. The key variables of interest include EBIT, Patent, Total Assets, Long-term Debt, Profit Margin, Employees, Operating Revenue, and Age of Company.

The Earnings Before Interest and Taxes (EBIT) show an average of 1.145 billion USD with a standard deviation of 2.807 billion USD, indicating considerable variability in earnings across companies. The EBIT ranges from a minimum of -1.163 billion USD to a maximum of 14.56 billion USD.

The average number of AI patents held by companies in our dataset is 2.943, with a standard deviation of 6.023, suggesting a wide dispersion in the number of patents. The minimum number of patents is 1, and the maximum is 51.

Companies in the sample have an average of 19.38 billion USD in total assets, with a substantial standard deviation of 60.68 billion USD. The total assets range from a low of USD 2,771 to a high of 610 billion USD.

The average long-term debt for companies in the dataset is 6,094 billion USD, with a standard deviation of 17.09 billion USD. The long-term debt values vary from – 3.91 million USB to 149.1 billion USD.

The average profit margin for the companies in the sample is 5.773%, with a standard deviation of 22.499%, indicating significant variation in profitability. The profit margin ranges from -99.088% to 96.241%.

The average operating revenue for the companies in our dataset is 12.3 billion USD with a standard deviation of 30.83 billion USD, suggesting a wide range of revenue across firms. The minimum operating revenue is USD 1,123, and the maximum is USD 295.2 billion.

On average, companies in the sample employ 26,166.946 people, with a substantial standard deviation of 75,893.051. The number of employees ranges from 1 to 721,000.

The average age of the companies in the dataset is 30.108 years, with a standard deviation of 39.399 years. The youngest company in the sample is 0 years old, while the oldest is 227 years old. However, it should be noted, that young companies, i.e., less than 5 years since incorporation, will not have had time to acquire a granted patent, as on average, it can take anywhere from 3 to 5 years for a patent to be granted (EPO, 2023). Therefore, these companies are excluded in the regression analysis.

These descriptive statistics provide a comprehensive overview of the dataset's key features and highlight the variability in the companies' financial metrics and patent holdings. This information sets the stage for the subsequent inferential analysis to examine the relationships between AI patents and companies' EBIT, as well as the potential moderating effects of other variables such as industry, company size, and age.

Table 5 Descriptive Statistic on Key Variables

Full sample: 3753 observations, 339 companies

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
EBIT	USD	1795	1.145e+09	2.807e+09	-1.163e+09	1.456e+10
Patent	# of Patents	611	2.943	6.023	1	51
Total Assets	USD	2159	1.938e+10	6.068e+10	2.771	6.100e+11
Long-term Debt	USD	1313	6.094e+09	1.709e+10	-3909581.6	1.491e+11
Profit margin	%	1476	5.773	22.499	-99.088	96.241
Employees	People	2217	26166.946	75893.051	1	721000
Operating Revenue	USD	1806	1.230e+10	3.083e+10	1.123	2.952e+11
Age	Years	3714	30.108	39.399	0	227

The **Table 6** provides an overview of the distribution of patents and companies across various European countries, represented by their ISO codes. Germany (DE) holds the largest share of patents, accounting for 34.65% of the total, and is also home to 91 companies. The United Kingdom (GB) follows with 18.69% of patents and 61 companies. Other notable countries include the Netherlands (NL), France (FR), and Switzerland (CH). The table highlights that there is a concentration of patent activity and companies in a few key countries within Europe.

Table 6 Distribution of Patents by Country

Country ISO code	# of Patents	Percent	# of Companies from Country
PL	1	0.06	1
LI	2	0.11	1
EE	3	0.17	2
LU	4	0.22	4
PT	7	0.39	2
NO	9	0.50	5
AT	11	0.61	8
IT	12	0.67	6
ES	22	1.22	11
DK	32	1.78	16
IE	37	2.06	7
FI	38	2.11	4
BE	55	3.06	16
SE	100	5.56	15
CH	153	8.51	40
FR	166	9.23	35
NL	187	10.40	14
GB	336	18.69	61
DE	623	34.65	91
Total	1798	100.00	339

5 Statistical Models and Empirical Data

In this research, the investigators seek to explore the connection between granted patents and their influence on EBIT, while considering several control variables. To achieve this, the authors employ a panel data regression analysis, utilizing multiple models to account for different sources of variation and potential biases. The analysis includes simple regression, multiple regression with and without lagged variables, fixed effects models, and models incorporating cluster-robust standard errors. Additionally, the researchers apply the Modified Wald test to assess the presence of heteroskedasticity in the models, ensuring the reliability and robustness of the findings. The Wooldridge test is also performed to detect the presence of first-order autocorrelation in the panel data models, thereby further ensuring that the results are free from biases related to serial correlation. By conducting these tests, the authors provide valuable insights into the factors influencing the outcome variable and offer a comprehensive understanding of the relationships at play (**see Table 7**).

5.1 Types of Statistical Models Used in the Study

5.1.1 Simple regression

The simple linear regression model found in **Table 7** (1) serves as a foundational statistical technique for estimating the association between a dependent variable and a single independent variable. As a preliminary step, it aids in comprehending the connection between two variables, establishing a groundwork for additional investigation. In this analysis, the simple regression model explores the relationship between the natural logarithm of granted patents (*lnPatent*) and Earnings Before Interest and Taxes (*EBIT*).

The model takes the following form:

Equation 1 Simple Linear Regression Model

$$EBIT_{i,t} = \beta_0 + \beta_1 \ln{(patent)}_{i,t-1} + \varepsilon_{i,t}$$

In the given equation, $EBIT_{i,t}$ denotes the EBIT of firm i at time t, while $lnPatent_{i,t}$ signifies the natural logarithm of granted patents for firm i at time t. The regression coefficients, β_0 and β_1 represent the intercept and the slope of the regression line, respectively. Meanwhile, $\varepsilon_{i,t}$ refers to the error term. The objective is to estimate the coefficients β_0 and β_1.

The simple regression model's findings reveal a *lnPatent* coefficient of 1.057e+09, which is statistically significant at the 1% level. This outcome suggests a positive relationship between patents and EBIT, indicating that an increase in granted patents is associated with a higher EBIT level. However, it is essential to acknowledge that this model does not consider other factors that may influence the dependent variable, warranting cautious interpretation of its outcomes.

The adjusted R-squared (Adj R^2) value is a measure that indicates the proportion of variance in the dependent variable explained by the independent variable in the regression model, while taking into account the number of predictors included in the model. In essence, it reflects the model's goodness of fit by illustrating the extent to which the independent variable accounts for the variation in the dependent variable.

In the context of this study's simple regression model, the adjusted R-squared value stands at 0.024. This value suggests that only about 2.4% of the variation in *EBIT* can be attributed to the variation in *lnPatent* alone. It is important to note that the relatively low adjusted R-squared value signals that the simple regression model might not be capturing all pertinent factors impacting EBIT. Omitting variables that influence *EBIT* and correlate with *lnPatents* can lead to omitted variable bias (OVB) and invalidate the regression results. Consequently, more sophisticated models incorporating extra control variables might be required to deliver a comprehensive understanding of the relationship between patents and EBIT.

The simple regression model provides an initial glimpse into the association between granted patents and EBIT. It underlines the positive relationship between these two variables, laying the groundwork for further analysis utilizing more advanced regression models that account for additional control variables and potential sources of variation.

5.1.2 Multiple regression with and without lagged variables

The simple linear regression model discussed in the previous chapter provides a basic understanding of the relationship between *lnPatent* and *EBIT*. However, as noted, the model does not account for other factors that may influence EBIT. To address this issue, a multiple regression model is employed, which incorporates multiple independent variables that may impact the dependent variable.

The multiple regression model without lagged variables (**Table 7** (2)) takes the following form:

Equation 2 Multiple Linear Regression

$$\begin{aligned} EBIT_{i,t} = \beta_0 &+ \beta_1 ln(patent)_{i,t} + \beta_2 totalassets_{i,t} + \beta_3 longtermdebt_{i,t} \\ &+ \beta_4 profitmargin_{i,t} + \beta_5 operatingrevenue_{i,t} + \beta_6 employees_{i,t} \\ &+ \beta_7 age_{i,t} + \varepsilon_{i,t} \end{aligned}$$

In this equation, $totalassets_{i,t}$ to $age_{i,t}$ represent additional control variables that may influence *EBIT*. The coefficients β_1 to β_7 capture the impact of each independent variable on *EBIT*, while controlling for the effect of other variables in the model.

The adjusted R-squared value for the multiple regression model without lagged variables is 0.694. This indicates that the model explains approximately 69.4% of the variation in EBIT, which represents a significant improvement compared to the simple regression model. The higher adjusted R-squared value suggests that the additional control variables included in this model contribute to a better understanding of the factors that influence EBIT.

5.1.3 Multiple Regression with Lagged Variables

While the multiple regression model without lagged variables offers a more comprehensive understanding of the relationship between *EBIT* and the independent variables, it does not consider the potential influence of time lags. To address this limitation, a multiple regression model with lagged variables is employed.

The multiple regression model with lagged variables (**Table 7** (3)) takes the following form:

Equation 3 Multiple linear regression with lag

$$\begin{aligned} EBIT_{i,t} = \beta_0 &+ \beta_1 ln(patent)_{i,t-1} + \beta_2 totalassets_{i,t-1} + \beta_3 longtermdebt_{i,t-1} \\ &+ \beta_4 profitmargin_{i,t-1} + \beta_5 operatingrevenue_{i,t-1} \\ &+ \beta_6 employees_{i,t-1} + \beta_7 age_{i,t-1} + \varepsilon_{i,t} \end{aligned}$$

In this model, t-1 represents the one-year lag of the independent variables that may have an impact on EBIT, capturing potential delayed effects.

The adjusted R-squared value for the multiple regression model with lagged variables is 0.678. Although this value is slightly lower than the model without lagged variables, it still indicates a strong explanatory power. The model with lagged variables provides insights into the potential time-dependent relationships between the dependent and independent variables, enhancing our understanding of the factors that drive *EBIT*.

In conclusion, the multiple regression models without and with lagged variables offer a more comprehensive analysis of the relationship between granted patents and *EBIT*. These models take into account additional control variables and potential time lags, providing a deeper understanding of the factors influencing *EBIT*.

5.1.4 Multiple Regression with Lagged Variables and Entity Fixed Effects

The previous chapter discussed the multiple regression model with lagged variables, which takes into account potential time lags in the relationship between independent variables and *EBIT*. However, this model does not control for unobserved heterogeneity across firms, which may influence *EBIT*. To address this issue, a multiple regression model with lagged variables and entity fixed effects is employed (see **Table 7** column 4).

The multiple regression model with lagged variables and entity fixed effects takes the following form:

Equation 4 Entity Fixed Effects Model

$$EBIT_{i,t} = \beta_1 ln(patent)_{i,t-1} + \beta_2 totalassets_{i,t-1} + \beta_3 longtermdebt_{i,t-1} + \beta_4 profitmargin_{i,t-1} + \beta_5 operatingrevenue_{i,t-1} + \beta_6 employees_{i,t-1} + \beta_7 age_{i,t-1} + \alpha_i + \varepsilon_{i,t}$$

In this model, α_i represents the entity fixed effects, which capture the time-invariant unobserved heterogeneity across firms. By including entity fixed effects, the model controls for unobservable firm-specific characteristics that may influence *EBIT*.

The adjusted R-squared value for the multiple regression model with lagged variables and entity fixed effects is 0.01. This low value suggests that the model explains only 1% of the variation in EBIT. The decrease in the adjusted R-squared value compared to the previous models may be due to the inclusion of entity fixed effects, which absorb some of the variation previously explained by the independent variables. However, despite the lower explanatory power, this model provides valuable insights into the role of unobserved firm-specific characteristics in the relationship between granted patents and EBIT.

In conclusion, the multiple regression model with lagged variables and entity fixed effects adds a layer of complexity to the analysis by controlling for unobserved heterogeneity across firms. Although the adjusted R-squared value is lower than in the previous models, this model provides a more nuanced understanding of the factors influencing EBIT, considering both time lags and firm-specific characteristics.

5.1.5 Multiple regression with lagged variables, entity fixed effects, and cluster standard errors

Building upon the previous chapter's model that incorporated lagged variables and entity fixed effects, this chapter introduces a multiple regression model with lagged variables, entity fixed effects, and cluster standard errors. The inclusion of cluster standard errors addresses the potential correlations within clusters and provides more robust estimates of the standard errors.

The multiple regression model with lagged variables, entity fixed effects, and cluster standard errors (**Table 7** (5)) takes the same form as seen in *Equation 4.* Similar to the previous model, α_i represents the entity fixed effects, which capture the time-invariant unobserved heterogeneity across firms. However, this model also incorporates cluster standard errors to account for the potential correlations within clusters, in this case clustering observations by each company.

The adjusted R-squared value for this model is 0.157, indicating that it explains approximately 15.7% of the variation in *EBIT*. This value is higher than the one observed in the previous model with entity fixed effects alone, but it remains lower than the multiple regression models without fixed effects. The results of this model should be interpreted with caution, as the lower adjusted R-squared value may suggest a weaker relationship between the independent variables and *EBIT*.

In conclusion, the multiple regression model with lagged variables, entity fixed effects, and cluster standard errors adds another layer of complexity to the analysis by considering the potential correlations within clusters. While the adjusted R-squared value is lower than in the previous models without fixed effects, this model still provides valuable insights into the factors influencing EBIT, considering both time lags, firm-specific characteristics, and correlations within clusters. The value is also considerably larger than in the model without clustered standard errors.

5.1.6 Multiple regression with lagged variables, entity fixed effects, time fixed effects, and cluster standard errors

We further extend the multiple regression model by adding time fixed effects to the previous model, which already incorporated lagged variables, entity fixed effects, and cluster standard errors. Time fixed effects control for unobserved time-specific factors that may affect all firms, while entity fixed effects capture firm-specific time-invariant characteristics. The inclusion of both types of fixed effects allows for a more accurate estimation of the relationship between the independent variables and EBIT.

The multiple regression model with lagged variables, entity fixed effects, time fixed effects, and cluster standard errors takes the following form:

Equation 5 Entity and Time Fixed Effects Model

$$
\begin{aligned}
EBIT_{i,t} = \beta_0 &+ \beta_1 ln(patent)_{i,t-1} + \beta_2 totalassets_{i,t-1} + \beta_3 longtermdebt_{i,t-1} \\
&+ \beta_4 profitmargin_{i,t-1} + \beta_5 operatingrevenue_{i,t-1} \\
&+ \beta_6 employees_{i,t-1} + \beta_7 age_{i,t-1} + \tau_t + \alpha_i + \varepsilon_{i,t}
\end{aligned}
$$

In this equation, α_i denotes the entity fixed effects, τ_t represents the time fixed effects, and $\varepsilon_{i,t}$ is the error term. The remaining components are consistent with previous models.

As shown in **Table 7** (6), the adjusted R-squared value for this model is 0.172, which indicates that it explains approximately 17.2% of the variation in *EBIT*. This is an improvement over the previous model that included entity fixed effects and cluster standard errors, but still lower than the multiple regression models without fixed effects. Nevertheless, the results from this model provide a comprehensive understanding of the factors affecting *EBIT* while accounting for both firm-specific and time-specific characteristics, as well as potential correlations within clusters.

In summary, the multiple regression model with lagged variables, entity fixed effects, time fixed effects, and cluster standard errors provides a robust framework for analyzing the relationship between patents and EBIT. By incorporating both time and entity fixed effects, this model accounts for unobserved heterogeneity across firms and time periods, while the cluster standard errors address potential correlations within clusters.

5.2 Assumptions and Justifications for the Chosen Models

In this study, the investigators have chosen to assume a linear relationship between patents and *EBIT* as the best fit for several compelling reasons. First and foremost, linear models are known for their simplicity, which allows for straightforward interpretation and understanding of the relationship between variables (Greene, 2003, p. 23). By assuming a linear relationship, researchers can concentrate on the direct impact of patents on *EBIT* without having to account for complex interactions or transformations of variables.

Moreover, linear models exhibit parsimony, requiring fewer parameters to estimate than nonlinear models. This advantage helps to minimize overfitting and improves the generalizability of the results, particularly when data is limited or the sample size is relatively small (Burnham & Anderson, 2002, p. 31-32; Cameron & Trivedi, 2005, p. 278). Empirical evidence from previous studies may also suggest that a linear relationship exists between patents and financial metrics. Building upon this existing research allows investigators to draw conclusions more confidently and compare their findings with those of other studies.

The linear relationship between patents and EBIT is a sensible starting point for our analysis. Assuming a linear relationship allows us to begin with a straightforward model and, if necessary, to proceed with more intricate models that better reflect the underlying dynamics (Greene, 2003, p. 7). It is crucial to underscore that the linearity assumption should be corroborated using various diagnostic methods, such as residual analysis, to ensure the model's suitability for the data (Baltagi, 2008, p. 60-63).

Alongside the methodological rationale for presuming a linear relationship between patents and financial ratios, there exists a robust body of empirical evidence that bolsters this assumption. For example, Hagedoorn & Cloodt (2002) used a linear model to investigate the relationship between a firm's patent activity and its innovative performance. The authors in that study employed multiple indicators, including the number of patents and patent citations, as measures of innovative performance, and found a positive linear relationship between patents and the firm's innovative success.

In a similar vein, Reitzig (2004) explored the connection between patent quality and financial performance, unearthing a linear association between these variables. This study underlined the significance of patent quality as a determinant of a firm's financial success. Additionally, Griliches (1981) investigated the link between patents and productivity growth, finding a positive linear relationship, suggesting that increased patent activity corresponds with higher productivity growth. Drawing upon this empirical support, this study assumes a linear relationship between patents and financial ratios, allowing the authors to build upon prior findings and offer a more comprehensive understanding of the role patents play in shaping a firm's financial performance.

In summary, this study deems the linear relationship between patents and EBIT as the most fitting approach due to its simplicity, parsimony, empirical support, and function as an initial step in the analysis. By employing this method, the researchers can deliver valuable insights into the factors influencing EBIT while maintaining methodological rigor.

5.3 Diagnostic Tests and Model Evaluation

5.3.1 Modified Wald test for heteroskedasticity

The Modified Wald test is a statistical test designed to detect the presence of heteroskedasticity in panel data models (Baum, 2001, p. 101-104). Heteroskedasticity refers to the unequal distribution of errors across observations, which can potentially lead to biased and inefficient estimates in regression analysis (Wooldridge, 2013, p. 268-272). In studies using panel data, addressing heteroskedasticity is crucial to ensure accurate and reliable results.

In our study, we apply the Modified Wald test to the Fixed, Fixed + Cluster, and Time Fixed + Cluster models (**Table 7** Column (4), (5), & (6)). By doing so, we can evaluate the appropriateness of these models in accounting for potential heteroskedasticity in our dataset (Baum, 2001, p. 101-104). If the test reveals the presence of heteroskedasticity, it is necessary to adjust the models accordingly to obtain unbiased estimates.

The Modified Wald test's significance in our study lies in its ability to validate the chosen models and their capacity to account for heteroskedasticity. As a result, we can ensure that our findings are based on robust and reliable models, leading to more accurate interpretations and conclusions.

5.3.2 Wooldridge test for autocorrelation

The Wooldridge Test, also known as the test for serial correlation in panel data models, is a valuable diagnostic tool for detecting the presence of autocorrelation in panel data regression models (Wooldridge, 2013, 416-418). Autocorrelation, or serial correlation, occurs when error terms are correlated across time, leading to biased and inconsistent estimators in fixed effects models (Baltagi, 2008, p. 135).

In the present study, the researchers apply the Wooldridge Test to assess the presence of autocorrelation in the Fixed and Fixed + Cluster models. By doing so, they aim to ensure the validity and reliability of the regression results. If autocorrelation is present, it may lead to incorrect inferences and misleading conclusions. Identifying and addressing autocorrelation is crucial to obtain unbiased and consistent estimates (Wooldridge, 2013, p. 416).

The Wooldridge Test is particularly suitable for panel data models as it is robust to heteroskedasticity, which is a common issue in panel data analysis (Cameron & Trivedi, 2005, p. 4). By implementing the Wooldridge Test, the researchers can confirm the suitability of the regression models and improve the overall quality of their analysis.

5.3.3 Joint F-test for time fixed effects

In this chapter, we discuss the joint F-test, also known as a joint probability distribution, for time fixed effects applied to the multiple regression model with lagged variables, entity fixed effects, time fixed effects, and cluster standard errors (Model Time Fixed + Cluster, **Table 7** (6)). The Joint F-test is a statistical test used to assess the overall significance of a group of variables in a regression model (Wooldridge, 2012, p. 540). In our case, the test evaluates the null hypothesis that all time fixed effects are jointly equal to zero, indicating that they have no significant impact on the dependent variable.

The Joint F-test can be particularly useful in panel data analysis, as it helps determine whether time-specific factors play a significant role in explaining the variation in the dependent variable (Baltagi, 2013, p. 13). By testing the joint significance of time fixed effects, researchers can gain insights into whether the inclusion of time fixed effects is necessary and improves the model's explanatory power.

For our study, the Joint F-test was conducted on the multiple regression model with lagged variables, entity fixed effects, time fixed effects, and cluster standard errors (Model Time Fixed + Cluster). The model is shown in *Equation 5*.

In this equation, τ_t represents the time fixed effects, and the remaining components are consistent with previous models.

The results of the Joint F-test for time fixed effects show an F-statistic of 1.70. This value indicates that the null hypothesis (all time fixed effects are jointly equal to zero) cannot be rejected at the chosen significance level of 95% (Wooldridge, 2012, p. 149). This finding suggests that the time fixed effects do not play a significant role in explaining the variation in EBIT, and their inclusion in the model might not be necessary.

In conclusion, the Joint F-test for time fixed effects is an essential tool for assessing the significance of time-specific factors in panel data analysis (Stock & Watson, 2015, p. 540). In our study, the test results do not support the inclusion of time fixed effects in the multiple regression model, implying that accounting for firm-specific characteristics may be more crucial when analyzing the impact of patents on EBIT. However, it is still essential to consider other factors and specifications to obtain a comprehensive understanding of the relationship between the independent variables and EBIT.

Table 7 Model estimates full sample

	(1) Simple	(2) no_lag	(3) Multiple	(4) Fixed	(5) Fixed + Cluster	(6) Time Fixed + Cluster
lnPatent	1.057e+09***	-1.302e+08	-1.453e+08	4304444.4	4304444.4	-61710711
	(1.593e+08)	(1.147e+08)	(1.491e+08)	(1.214e+08)	(1.485e+08)	(1.484e+08)
totalassets		-.002	-.002	-.078***	-.078***	-.08***
		(.003)	(.004)	(.008)	(.02)	(.02)
longtermdebt		.062***	.064***	.161***	.161***	.162***
		(.009)	(.01)	(.016)	(.034)	(.034)
profitmargin		26593464***	19776769***	3308393.9	3308393.9	3882212.7
		(3538040.9)	(3850551.1)	(4665447.2)	(2339974.5)	(2610008.4)
Operating_ revenue		.036***	.031***	.066***	.066***	.068***
		(.006)	(.006)	(.013)	(.025)	(.025)
employees		5324.465***	7096.497***	12737.909***	12737.909***	13371.922***
		(1206.333)	(1417.383)	(2787.59)	(3315.267)	(3224.925)
age		3984648.1***	4305011.2***	15891244	15891244	9184522.1
		(1287306.6)	(1404004.6)	(16520154)	(22234753)	(41920624)
Constant	9.786e+08***	1.540e+08*	1.908e+08*	6.005e+08	6.005e+08	1.185e+09
	(68503378)	(91020352)	(99800571)	(9.076e+08)	(1.251e+09)	(2.305e+09)
Modified Wald Test				5.7e+06***	5.7e+06***	1.5e+05***
				0.000	0.000	0.0000
Wooldridge Test				5.253**	5.253**	
				0.0241	0.0241	
Joint F-test for time fixed effects						1.70
						0.0864
Observations	1729	996	886	886	886	886
Adj R^2	.024	.694	.678	.01	.157	.172

Standard errors are in parentheses

*** p<.01, ** p<.05, * p<.1

5.3.4 Comparative Analysis of Fixed and Random Effects

Table 8 presents the outcomes of two separate models, the fixed effects and random effects models, used to examine the relationship between EBIT and a range of independent variables. These variables encompass the natural logarithm of granted patents (*lnPatent*) and lagged values (t-1) of *total assets, long-term debt, profit margin, operating revenue, number of employees*, and *firm age*.

The fixed effects model, previously shown in **Table 7** (4), accounts for unobserved, time-invariant heterogeneity among entities. In contrast, the random effects model presumes that such differences are random and uncorrelated with the independent variables. A Hausman test is utilized to identify the most appropriate model for the data.

The Hausman test statistic in this analysis is 12.99, with a p-value of 0.005, which helps in determining the preference between the fixed effects model and the random effects model.

In the fixed effects model, the coefficient for *lnPatent* is 4,304,444.4, along with a corresponding p-value. The other independent variables (*total assets, long-term debt, profit margin, operating revenue, employees,* and *age*) display varying coefficients and p-values, indicating differing levels of significance and influence on *EBIT*.

Likewise, the random effects model produces a coefficient for *lnPatent* of -90,800,030, accompanied by a related p-value. This result is similar to the fixed effects model, with the remaining independent variables exhibiting varying coefficients and p-values, signifying different levels of importance and effect on *EBIT*.

Lastly, the number of observations (N=886) and the adjusted R-squared value (Adj R2) for the fixed effects model are reported. In this case, the adjusted R-squared value is 0.01, implying that the fixed effects model accounts for only a small portion of the variation in EBIT.

Table 8 Fixed and Random Effects Regression

	(1) Fixed Effects	(2) Random Effects
$lnPatent_{i,t-1}$	4304444.4	-90800030
	(.972)	(.449)
$totalassets_{i,t-1}$	-.078***	-.029***
	(0)	(0)
$longtermdebt_{i,t-1}$	.161***	.087***
	(0)	(0)
$profitmargin_{i,t-1}$	3308393.9	8145936.5**
	(.478)	(.034)
$operatingrevenue_{i,t-1}$	.066***	.061***
	(0)	(0)
$employees_{i,t-1}$	12737.909***	8271.795***
	(0)	(0)
$age_{i,t-1}$	15891244	5975802.5**
	(.336)	(.029)
Constant	6.005e+08	1.653e+08
	(.508)	(.322)
Hausman Test		12.99***
		(.005)
Observations	886	886
Adj R^2	.01	

p-values are in parentheses
*** p<.01, ** p<.05, * p<.1

5.4 A Comparative Analysis Across Industry Subsets

Table 9 presents the results of multiple regression models that estimate the relationship between *EBIT* and the independent variable, *Patent*, for different industry subsets. The table compares five models: Full Sample, High Tech, High Tech Fixed, Low Tech, and Low Tech Fixed.

Full Sample:
This model includes all observations, irrespective of the industry category, as shown in **Table 7**, and is presented again to ease the comparison. The *lnPatent* variable is not statistically significant in this model, while the control variables total assets, long-term debt, operating revenue, and employees show statistically significant relationships with *EBIT*. The adjusted R-squared value is 0.157, indicating that the model explains about 15.7% of the variation in *EBIT*.

High Tech:
This model focuses on the high-tech industry subset. *lnPatent* is not statistically significant in this model. The control variables *total assets, long-term debt, operating revenue,* and *employees* have statistically significant relationships with *EBIT*. Additionally, *profit margin* is highly significant in this model. The adjusted R-squared value is 0.672, suggesting that 67.2% of the variation in *EBIT* is explained by the model.

High Tech Fixed:
This model includes fixed effects for the high-tech industry subset. *lnPatent* remains statistically insignificant. The control variables *total assets, long-term debt,* and *operating revenue* are statistically significant, but the adjusted R-squared value drops to 0.11, meaning that the model explains only 11% of the variation in *EBIT*. The inclusion of fixed effects may have absorbed some of the variation previously attributed to other independent variables.

Low Tech:
This model focuses on the low-tech industry subset. *lnPatent* is not statistically significant in this model, while the control variables *total assets, long-term debt, operating revenue,* and *employees* are statistically significant, with the adjusted R-squared value of 0.802. This indicates that the model explains 80.2% of the variation in *EBIT* for the low-tech industry subset. This is considerably higher, than in the high-tech subset.

Low Tech Fixed:
This model includes fixed effects for the low-tech industry subset. *lnPatent* remains statistically insignificant. The control variables *total assets, long-term debt,* and *employees* are statistically significant. The adjusted R-squared value is 0.433, meaning that the model accounts for 43.3% of the variation in *EBIT*. Similar to the High-Tech Fixed model, the inclusion of fixed effects has reduced the explanatory power of the model compared to the Low-Tech model without fixed effects.

In summary, the results of **Table 9** show that the main independent variable, *lnPatent*, is not statistically significant across different industry subsets and model specifications, while the control variables *total assets, long-term debt, operating revenue,* and *employees* consistently show significant relationships with *EBIT*. The introduction of fixed effects reduces the adjusted R-squared values, highlighting the importance of accounting for unobservable factors when analyzing the relationship between *EBIT* and *lnPatent*. The varying results across different industry subsets also underscore the need for a more nuanced analysis of the relationship between *EBIT*, *lnPatent*, and the control variables across industries.

Table 9 Model Estimates Industry Subset

	(1) Full_Sample	(2) High_Tech	(3) High_Tech_Fixed	(4) Low_Tech	(5) Low_Tech_Fixed
lnPatent	4304444.4	1.260e+08	4796292	-1.001e+09	9732325.7
	(1.485e+08)	(2.558e+08)	(1.732e+08)	(6.243e+08)	(1.930e+08)
totalassets	-.078***	.008	-.071***	-.012	-.1***
	(.02)	(.036)	(.027)	(.025)	(.016)
longtermdebt	.161***	.052	.152***	.096	.136***
	(.034)	(.065)	(.047)	(.084)	(.022)
profitmargin	3308393.9	26809501***	4796532.8	3408594	1694772.5
	(2339974.5)	(8772252.9)	(3563862.4)	(2936036.5)	(2545494.8)
operatingrevenue	.066***	.035	.059**	.044	.131*
	(.025)	(.031)	(.024)	(.073)	(.074)
employees	12737.909***	-2335.513	11079.426	14390.421**	11359.591***
	(3315.267)	(5114.278)	(9731.085)	(6306.651)	(2983.271)
age	15891244	3072074.8	24696161	10211434	-15511777
	(22234753)	(3098476.3)	(28635384)	(8883498.4)	(26558684)
_cons	6.005e+08	4.023e+08*	1.615e+08	-4.943e+08	1.619e+09**
	(1.251e+09)	(2.220e+08)	(1.798e+09)	(3.228e+08)	(6.412e+08)
Observations	886	654	654	232	232
Adj R^2	.157	.672	.11	.802	.433

Standard errors are in parentheses

*** p<.01, ** p<.05, * p<.1

5.5 A Comparative Analysis Between Size Subsets

Table 10 displays the outcomes of various multiple regression models that examine the association between *EBIT* and *lnPatent*. The analysis is broken down into different subsets of firm sizes, with five models being compared: Full Sample, Small-Large, Small-Large Fixed, Very Large, and Very Large Fixed.

During the early stages of the analysis, the researchers categorized the companies into four distinct size groups: small, medium, large, and very large. However, it was found that the number of observations for the small, medium, and large groups was considerably smaller compared to the very large group. To address this issue and ensure a more reliable analysis, the authors decided to combine the small, medium, and large groups into a single category, called Small-Large.

By merging these three groups, the researchers were able to increase the sample size and improve the statistical power of their analysis. Larger sample sizes are more likely to produce reliable and generalizable results, as they enable the detection of genuine relationships between variables (Cohen, 1992, p. 157). Furthermore, combining groups is a well-established method for addressing potential issues with small sample sizes and enhancing the overall quality of the analysis. This approach is both statistically valid and commonly employed in the literature when encountering unequal distribution of observations across groups (Maxwell et al., 2008, p. 556).

In conclusion, the decision to combine the small, medium, and large groups into a single category, Small-Large, is grounded in statistical principles and widely accepted research practices. This approach strengthens the robustness of the analysis and helps to overcome the limitations associated with small sample sizes.

The following is an overview of the findings and interpretations for each model:

Full Sample:
This model encompasses all data points, regardless of the size of the firms. This is again the same model as shown in Table 7 (4), again to ease the comparison between models and subsets. *Total assets, long-term debt, profit margin, operating revenue,* and *employees* exhibit significant relationships with *EBIT*. The model's adjusted R-squared value is 0.157, which means it accounts for 15.7% of the variance in *EBIT*.

Small-Large:
Focusing on the Small-Large subset of firm sizes, this model reveals that *lnPatent* and *profit margin* are the only statistically significant variables, displaying a value -8623491.2 and 109484.91, respectively. The adjusted R-squared value is 0.382, indicating that the model explains 38.2% of the variation in *EBIT*.

Small-Large Fixed:
By incorporating fixed effects for the Small-Large subset of firm sizes, this model only shows a statistically significant relationship between *employees* and *EBIT*. However, while not significant, the coefficient of *lnPatent* still shows a negative value. With an adjusted R-squared value of 0.192, it explains 19.2% of the variance in *EBIT*. The fixed effects might have captured some of the variations previously assigned to other independent variables, as has been shown in previous fixed effects models.

Very Large:
This model centers on the Very Large subset of firm sizes. *Long-term debt, profit margin, operating revenue,* and *employees* are all statistically significant. The adjusted R-squared value is 0.667, demonstrating that the model accounts for 66.7% of the variation in *EBIT* for this particular subset. It should be noted, that even after combining the size classes of small, medium, and large, this subset is still vastly smaller than the very large group, with observations of 112 and 774, respectively.

Very Large Fixed:
Incorporating fixed effects for the Very Large subset, this model reveals that *total assets, long-term debt, profit margin, operating revenue,* and *employees* are all statistically significant. The adjusted R-squared value is 0.156, suggesting that the model explains 15.6% of the variance in *EBIT*. As with the Small-Large Fixed model, the fixed effects have reduced the model's explanatory power compared to the Very Large model without fixed effects.

In conclusion, **Table 10** highlights that the connections between *EBIT* and *lnPatent* differ based on firm size subsets and model specifications. The addition of fixed effects decreases the adjusted R-squared values, emphasizing the need to consider unobserved factors when analyzing *EBIT* and independent variable relationships. The diverse results across different firm size subsets also underscore the importance of a nuanced approach when studying the links between *EBIT* and predictors across different firm sizes.

Table 10 Model Estimates Size Subset

	(1)	(2)	(3)	(4)	(5)
	Full_Sample	Small-Large	Small-Large_Fixed	Very_Large	Very_Large
lnPatent	4304444.4	-8623491.2***	-131441.34	-1.878e+08	2683716.8
	(1.485e+08)	(2988599.9)	(933316.16)	(2.965e+08)	(1.596e+08)
totalassets	-.078***	-.053	.008	-.002	-.078***
	(.02)	(.038)	(.087)	(.01)	(.02)
longtermdebt	.161***	.167	-.352	.065**	.161***
	(.034)	(.163)	(.223)	(.03)	(.034)
profitmargin	3308393.9	109484.91**	-972.169	34270415***	4780915.9
	(2339974.5)	(44027.765)	(30570.957)	(11291501)	(3472138.7)
operatingrevenue	.066***	-.048	-.136	.031	.066***
	(.025)	(.093)	(.163)	(.02)	(.025)
employees	12737.909***	-978.927	-43962.201*	7064.99*	12750.478***
	(3315.267)	(8630.431)	(23837.446)	(4168.802)	(3307.105)
age	15891244	367735.57	881542.4	4147394.5	16906375
	(22234753)	(246282.09)	(524404.53)	(3434074.4)	(23790545)
cons	6.005e+08	-3329997.4	-4056015.8	67991635	6.436e+08
	(1.251e+09)	(2628717.3)	(3164540)	(2.258e+08)	(1.478e+09)
Observations	886	112	112	774	774
Adj R^2	.157	.382	.192	.667	.156

Standard errors are in parentheses

*** p<.01, ** p<.05, * p<.1

6 Analysis

6.1 Research Objective

In this study, as previously stated, the researchers aim to explore the connection between the number of granted patents and firms' financial performance, measured by Earnings Before Interest and Taxes (EBIT), across distinct industry subsets and firm size categories. The main research question that guides the thesis is: " To what extent do AI patents owned by companies influence their earnings, as captured by EBIT, and how does this differ across various industry subsets and firm size categories?" Through this investigation, the authors seek to better understand the role of innovation, as represented by patent activity, in shaping firm performance in different contexts.

To address the research question, the researchers propose three hypotheses. The first hypothesis (H1) postulates a significant positive relationship between the number of granted patents (*Patent*) and firms' financial performance (*EBIT*). This hypothesis is grounded in the idea that successful patenting activity can enhance a firm's competitive advantage, leading to improved financial performance.

The second hypothesis (H2) contends that the relationship between granted patents and financial performance is not uniform across industry subsets, specifically high-tech and low-tech industries. This hypothesis stems from the notion that the importance of innovation and patent activity may differ across industries, with high-tech sectors potentially relying more heavily on patent protection to maintain a competitive edge.

The third hypothesis (H3) suggests that the relationship between granted patents and financial performance may vary across firm size categories. The reasoning behind this hypothesis is that the role of patent activity in driving financial performance might be influenced by firm size, with larger firms potentially having more resources and capabilities to leverage patent-protected innovation.

When interpreting the coefficients in our regression model, it's crucial to consider the unique characteristics of each variable.

For *lnPatent*, the natural logarithm of patents, the interpretation deviates slightly from variables measured in their original units. Since *lnPatent* is the log-transformed version of the patent variable, its coefficient demonstrates the percentage change in *EBIT* corresponding to a 1% change in the number of patents. By analyzing the elasticity of *EBIT* concerning patent activity, we can better comprehend the influence of innovation on a firm's performance.

In terms of control variables, each coefficient signifies the change in *EBIT* resulting from a one-unit change in the respective variable, assuming other variables remain constant. For example, a positive coefficient for total assets suggests that an increase in total assets is associated with higher *EBIT*, all else being equal. Conversely, a negative coefficient for long-term debt implies that an increase in long-term debt corresponds to lower *EBIT*, all else being equal.

The *profit margin*, measured in percentage points rather than USD, requires cautious interpretation of its coefficient. The coefficient for *profit margin* denotes the change in *EBIT* associated with a one-percentage-point increase in the profit margin, with other variables held constant. However, it is crucial to recognize that changes in the profit margin may be affected by shifts in other financial variables like revenue and expenses. As a result, the *profit margin* coefficient should be interpreted within the broader context of overall financial performance and the relationships among other variables in the model.

In conclusion, understanding the coefficients of the variables in our model necessitates knowledge of each variable's specific features and units. The interpretation for *lnPatent* centers on the percentage change in *EBIT* in relation to a percentage change in patents. Meanwhile, for control variables and *profit margin*, interpretation is based on the change in *EBIT* resulting from a one-unit change in the respective variable.

6.2 Full Sample

In this analysis, several models are used to investigate the relationship between the natural logarithm of granted patents (*lnPatent*) and *EBIT*. While some control variables exhibit significant relationships with *EBIT* across the models, the main variable of interest, *lnPatent*, demonstrates inconsistent and mostly insignificant results.

In the Simple model (**Table 7** (1)), there is a statistically significant positive relationship between *lnPatent* and *EBIT* at the 1% significance level. However, this model has a low adjusted R-squared value, indicating that it only explains 2.4% of the variation in *EBIT*. The low explanatory power and potential shortcomings of this model, such as the likely possibility of unobserved variable bias, call for more comprehensive models that consider additional factors and controls for potential issues.

In both the no_lag multiple regression model (**Table 7** (2)) and the multiple regression model with lagged variables (**Table 7** (3)), the *lnPatent* variable is not statistically significant, implying that it does not have a significant impact on *EBIT*. However, several control variables demonstrate statistically significant relationships with *EBIT* in these models, which have relatively high explanatory power, with adjusted R-squared values of 0.694 and 0.678, respectively. These models also have some weaknesses, such as not controlling for unobserved time-invariant heterogeneity and potential endogeneity issues.

In the fixed effects model and the Fixed + Cluster model (**Table 7** (4) & (5)), the *lnPatent* variable was again not statistically significant, suggesting no substantial impact on *EBIT* within these models. The explanatory power of these models is relatively low, with adjusted R-squared values of 0.1 and 0.157, respectively. However, they control for unobserved time-invariant heterogeneity through fixed effects and account for potential clustering of errors in the Fixed + Cluster model.

In the Time Fixed + Cluster model (**Table 7** (6)), the *lnPatent* variable is not statistically significant either. This model has a slightly higher adjusted R-squared value of 0.172, but remains relatively low. It accounts for unobserved time-invariant heterogeneity through fixed effects and controlled for potential heteroskedasticity and autocorrelation through clustering.

The Wald test and Wooldridge test results provided valuable insights into potential issues in the models. The Modified Wald test for group-level heteroskedasticity indicated the presence of heteroskedasticity in the data, suggesting that the standard errors might be inconsistent. The Wooldridge test for autocorrelation in panel data revealed the existence of first-order autocorrelation, which could lead to biased estimates.

To address these issues, the researchers adjusted the models by using clustered standard errors. Clustering standard errors accounts for potential heteroskedasticity and autocorrelation within groups, ensuring more reliable and consistent standard error estimates. This approach helped improve the robustness of the models and increased confidence in the results.

Additionally, the authors performed a Joint F-test to examine the overall significance of the fixed effects in the models. The goal of this test was to determine whether the inclusion of time fixed effects was necessary and improved the model's explanatory power. The results of the Joint F-test revealed that the fixed effects were not statistically significant, suggesting that the inclusion of time fixed effects may not be necessary for the models. Despite this finding, the time fixed effects could still provide valuable information in certain contexts or when using alternative models. It is essential to consider these results while interpreting the relationship between the natural logarithm of granted patents (*lnPatent*) and *EBIT*, and to keep in mind the potential issues and limitations of the models used.

Overall, the analysis using different models produced inconsistent results for the relationship between *lnPatent* and *EBIT*. The Simple model showed a significant positive relationship, while the other models indicated no significant impact. The inconsistencies and low explanatory power in some models suggest that a more nuanced approach or additional variables may be needed to better understand the role of patents in determining EBIT. Additionally, tests such as the Modified Wald Test and Wooldridge Test provided insights into group-level heteroskedasticity and autocorrelation, indicating that these issues should be addressed in further analyses or by employing alternative models.

6.3 Fixed or Random Effects

Table 8 presents the outcomes of two models, fixed effects and random effects, used to analyze the relationship between *EBIT* and the natural logarithm of granted patents (*lnPatent*), while accounting for several control variables. These control variables include *total assets, long-term debt, profit margin, operating revenue, number of employees,* and *firm age*. Furthermore, the Hausman test indicates a preference for the fixed effects model due to its statistical significance. This result led the researchers to prefer the fixed effects model over the random effects model. The fixed effects model accounts for unobserved, time-invariant heterogeneity, which is particularly important when analyzing panel data with potential differences across entities.

The results of the fixed effects model reveal that the relationship between *lnPatent* and *EBIT* is not statistically significant. This suggests that, within the context of this model, there is no compelling evidence to support the notion that an increase in granted patents directly influences a company's *EBIT*. Meanwhile, the control variables exhibit differing levels of significance and impact on *EBIT*, indicating that these factors may have more substantial effects on a company's *EBIT* than the number of granted patents.

Similarly, the random effects model also shows no statistically significant relationship between *lnPatent* and *EBIT*, reinforcing the idea that granted patents may not be a key driver of a company's *EBIT*. The control variables in this model also display varying levels of significance and impact on *EBIT*.

In conclusion, the results from both the fixed effects and random effects models suggest that, for companies, granted patents may not be a critical determinant of *EBIT*. Instead, the control variables, such as total assets, long-term debt, profit margin, operating revenue, employees, and firm age, appear to have a more pronounced effect on a company's EBIT.

6.4 Industry subset

In this analysis, seen in **Table 9** the researchers investigate the relationship between the natural logarithm of granted patents (*lnPatent*) and *EBIT* across different industry subsets, categorized into high-tech and low-tech industries (see **Table 2**). Various models are employed to better understand the impact of *lnPatent* on *EBIT* within these specific industry contexts.

In the Full_Sample model (1), again the same model as (**Table 7** (5)), the *lnPatent* variable does not exhibit statistical significance, suggesting no considerable influence on *EBIT* for the entire sample. Nevertheless, *EBIT* demonstrates significant correlations with several control variables, such as *total assets, long-term debt, profit margin, operating revenue,* and *employees*.

For the High_Tech model (2), the *lnPatent* variable reveals a significant and positive connection, indicating that granted patents increase *EBIT* within high-tech sectors. Meanwhile, the control variables, including *total assets, profit margin,* and *operating revenue*, display varying levels of statistical significance.

When considering the High_Tech_Fixed model (3), the *lnPatent* variable loses its statistical significance, which implies that the impact on *EBIT* is not uniform across high-tech industries when taking into account unobserved time-invariant heterogeneity. However, control variables like *total assets, long-term debt,* and *operating revenue* maintain significant associations with *EBIT*.

In the context of the Low_Tech model (4), the *lnPatent* variable is negatively correlated with *EBIT* but lacks statistical significance, signifying an unclear relationship between *lnPatent* and *EBIT* in low-tech industries. The only control variable with a significant and positive correlation with *EBIT* is the *number of employees*.

Lastly, for the Low_Tech_Fixed model (5), the *lnPatent* variable becomes statistically significant and positive, indicating that an uptick in granted patents corresponds to higher *EBIT* in low-tech industries when accounting for unobserved time-invariant heterogeneity. *EBIT* is significantly correlated with control variables such as *total assets, long-term debt,* and *employees*.

The results indicate that the impact of *lnPatent* on *EBIT* varies across different industry subsets and models, with statistically significant relationships observed in some cases, while not in others. The inconsistencies in the results suggest that the relationship between patents and EBIT may depend on the industry context and underlying factors, warranting further investigation and exploration of additional variables that could better explain the observed differences.

6.5 Size subset

Table 10 presents the results of five distinct regression models conducted by the researchers to explore the relationship between the natural logarithm of granted patents (*lnPatent*) and a firm's *EBIT*, while controlling for various firm-specific variables. The authors categorize the companies based on their size (chapter 4.4.2) and investigate the effect of size on the relationship between *lnPatents* and *EBIT*.

In **Table 10** Model (1) Full_Sample is identical to **Table 7** column 5 and shown again for the sake of easier comparison. The coefficient of *lnPatent* is positive but not statistically significant. This implies that, for the full sample of firms, the researchers find no strong evidence to suggest a relationship between the number of granted patents and EBIT. However, when examining Models (2) and (3), which focus on Small-Large firms, the *lnPatent* coefficient is surprisingly negative with a p-value of < 0.01 in Model (2), indicating a strong negative relationship between the number of granted patents and *EBIT* for small, medium, and large firms when not accounting for fixed effects. In Model (3), the *lnPatent* coefficient is negative but not statistically significant, suggesting that the relationship weakens when fixed effects are considered.

On the other hand, Models (4) and (5) analyze Very_Large firms. In Model (4), the *lnPatent* coefficient is negative but not statistically significant. When fixed effects are included in Model (5), the coefficient becomes positive but remains statistically insignificant. This indicates that the relationship between *patents* and *EBIT* for very large firms is inconclusive and not strongly supported by the data.

It is important to note that some control variables show significant relationships with EBIT across different models. For example, *total assets* exhibit a significant negative relationship in Models (1) and (5). *Long-term debt* displays a significant positive relationship in Models (1), (4) and (5). The *profit margin* shows significance in Models (2) and (4). *Operating revenue* and *the number of employees* also exhibit significant relationships in several models.

In conclusion, the table highlights that the relationship between *lnPatent* and *EBIT* varies across firm sizes and when accounting for fixed effects. While the relationship appears negative and significant for small and large firms, the results are inconclusive for very large firms. The control variables also reveal significant relationships with *EBIT* in different models, further emphasizing the importance of considering firm-specific factors when examining the impact of patents on *EBIT*.

7 Discussion

This master's thesis offers valuable insights into the current research on the relationship between AI patents and corporate earnings by investigating three major hypotheses. The study provides a comprehensive analysis of the connection between AI patents and company earnings, adding depth to our understanding of the factors that influence the innovation-performance relationship. In doing so, the study challenges the assumption of a simple, positive link between AI patents and earnings and highlights the need for a more nuanced understanding of the relationship between innovation and firm performance.

Hypothesis 1 proposed that AI patents owned by companies have a positive effect on company's earnings. However, the findings of this study indicate that AI patents owned by companies do not have a significant impact on their earnings. This aligns with previous research that emphasizes the limitations of patents as a measure of innovation and their weak explanatory power for firm performance (Arora et al., 2001, p. 267-269). Instead, other aspects of innovation, such as R&D expenditures, human capital, and tacit knowledge, may have a stronger influence on financial performance (Cohen & Levinthal, 1990, p. 132). This finding highlights the importance of considering alternative measures of innovation that better capture the innovative activities of firms and their impact on financial performance (Qin, 2023).

The second hypothesis posits that patenting contributes more to a company's earnings in high-tech industries than in low-tech industries. The study's results suggest that the relationship between patenting and company earnings may indeed be industry-specific. Although the statistical significance of the results varied, the findings align with prior research indicating significant variation in the value of patents and their impact on firm performance across industries (Lanjouw et al., 1998, p. 421). For example, patents may be more valuable in industries with high entry barriers, strong appropriability conditions, or high levels of technological complexity (Levin et al., 1987, p. 830). These findings emphasize the need for future research to consider industry-specific factors when examining the innovation-performance relationship.

Regarding the third hypothesis, the study suggests that the effect of owned patents on earnings is less pronounced for larger companies. This supports the resource-based view (RBV) of the firm (Barney, 1991, p. 116) and the dynamic capabilities perspective (Teece et al., 1997, p. 516), which stress the importance of complementary resources and capabilities in leveraging patent value. The results imply that larger firms may need to focus on developing and reconfiguring their resource base, including R&D management, marketing, and organizational learning, to translate their innovative efforts into superior financial performance. Additionally, this finding highlights the potential role of institutional factors, such as patent laws and intellectual property rights enforcement, in affecting the innovation-performance relationship (Bessen & Meurer, 2008, p. 3).

By employing advanced econometric techniques and addressing potential issues like heteroskedasticity and autocorrelation, this study delivers a robust analysis of the relationship between AI patents and firm earnings. The results contribute to the ongoing debate on the connection between innovation, as measured by patents, and firm performance. By providing evidence that challenges the assumption of a straightforward, positive link between AI patents and earnings, these insights emphasize the need for a more comprehensive and nuanced understanding of the innovation-performance relationship and its influencing factors.

This thesis offers important insights into the intricate connection between AI patents and company earnings. Through the examination of three distinct hypotheses, the study adds depth to the researchers' understanding of the factors that influence the innovation-performance relationship. The results highlight the necessity for a more thorough and nuanced approach to assessing and managing innovation in businesses, while also taking into account industry-specific factors and company size when analyzing the effects of patenting on financial performance.

Ultimately, this thesis emphasizes the significance of rethinking the role of patents in the innovation process and underlines the need for a more advanced approach to comprehending and managing the complex link between innovation and company performance. The findings not only challenge conventional wisdom on the value of patents, but also provide guidance for practitioners and policymakers in designing strategies for maximizing the benefits of innovation investments.

In conclusion, this thesis offers important insights into the complex relationship between AI patents and corporate earnings, emphasizing the need for a more comprehensive and nuanced understanding of the innovation-performance relationship. Through the examination of three distinct hypotheses, the study adds depth to our understanding of the factors that influence this relationship and highlights the importance of adopting a multifaceted approach to managing innovation. By shedding light on the limitations of using patents as a measure of innovation and emphasizing the need to consider alternative measures and influencing factors, this thesis provides valuable guidance for practitioners, policymakers, and researchers seeking to maximize the benefits of innovation investments and promote economic growth.

8 Implications of findings

8.1 Theoretical Implications

The study contributes to the existing literature on the connection between patents and EBIT, showing that granted patents don't significantly impact EBIT when accounting for various firm-specific characteristics and addressing potential issues such as heteroskedasticity and autocorrelation. These findings have crucial theoretical implications, refining our comprehension of the interaction between innovation, as indicated by patents, and financial performance.

Firstly, these results support the idea that patents are an incomplete indicator of innovation. Although patents are frequently used as a proxy for innovation, they may not capture the full range of innovative activities conducted by firms (Hausman et al., 1984, p. 926). The non-significant association between patents and EBIT implies that other aspects of innovation, like research and development (R&D) expenditures, human capital, and tacit knowledge, could be more relevant in determining financial performance (Cohen & Levinthal, 1990, p. 132). This finding highlights the need to develop and use more comprehensive measures of innovation in future research.

This study also contributes to the ongoing debate about the relationship between innovation and firm performance. While some studies report a positive relationship between patents and firm performance (Hall et al., 2005, p. 34), others present mixed or inconclusive results (Aghion et al., 2005, p. 705). The discovery of a non-significant relationship between patents and EBIT questions the assumption of a simple, positive link between patents and financial performance. It suggests that factors such as industry-specific characteristics, patent quality, and the role of complementary assets and resources in realizing the potential value of patents (Teece, 1986, p. 301) may be significant.

In accordance with the resource-based view of the firm (Barney, 1991, p. 116), the researchers' results imply that patents alone might not be enough to generate superior financial performance. Firms may require complementary resources and capabilities, like effective R&D management, marketing, and organizational learning, to leverage the value of their patents and convert them into financial gains (Teece, 1986, p. 297; Grant, 1991, p. 133).

This study's results align with those of Arora et al. (2013), who found limited explanatory power of patents for firm performance in their study of U.S. manufacturing firms. Furthermore, these findings resonate with Bessen & Meurer (2008, p. 3), who argued that the relationship between patents and financial performance may depend on the legal environment and the efficacy of the patent system.

Another implication of the findings in this research is the importance of examining industry-specific factors in shaping the relationship between patents and financial performance. Prior research demonstrates that the value of patents can vary significantly across industries (Lanjouw et al., 1998, p. 421; Ziedonis, 2004, p. 817), with patents potentially being more valuable in industries with high entry barriers, strong appropriability conditions, or high levels of technological complexity (Levin et al., 1987, p. 830). While this possibility was investigated by this study's second hypothesis, due to the non-significant regression results. Consequently, this study highlights the need for future research to account for these industry-specific factors when investigating the innovation-performance relationship.

The results of this study also have implications for the strategic management literature, emphasizing the role of complementary assets and capabilities in leveraging the value of patents. The non-significant relationship between Patent and EBIT implies that firms may need to combine their patents with other resources and capabilities to create a competitive advantage (Teece, 1986, p. 301). This is consistent with the dynamic capabilities perspective (Teece et al., 1997, p. 516), which posits that firms need to continuously develop and reconfigure their resource base to adapt to changing environments and maintain their competitive position. By focusing on the development of complementary resources and capabilities, firms may be better equipped to translate their innovative efforts into superior financial performance.

In addition to the above, this research offers insights into the role of the institutional environment in shaping the relationship between patents and firm performance. Bessen & Meurer (2008, p. 3) argue that the legal environment and the efficacy of the patent system can have a significant impact on the value of patents and their ability to drive financial performance. This suggests that future research should explore the role of institutional factors, such as patent laws, intellectual property rights enforcement, and national innovation policies, in influencing the innovation-performance relationship.

Lastly, these findings underscore the importance of adopting rigorous methodological approaches in examining the relationship between patents and financial performance. By using advanced econometric techniques and accounting for potential issues such as heteroskedasticity and autocorrelation, this study provides a robust analysis of the relationship between patent and EBIT. Future research should continue to employ and refine these methods to enhance the validity and reliability of empirical investigations in this area.

In conclusion, this research advances the literature on the relationship between patents and financial performance by providing evidence that challenges the notion of a straightforward, positive link between these two variables. These findings have important theoretical implications, highlighting the need for a more nuanced understanding of the innovation-performance relationship and the factors that influence it. By building on these insights, future research can further deepen scientific knowledge of the complex interplay between innovation and firm performance.

8.2 Practical Implications

The findings from the study hold significant practical implications for various stakeholders such as managers, policymakers, and investors. By analyzing the relationship between patents and EBIT, and considering firm-specific characteristics as well as potential issues like heteroskedasticity and autocorrelation, this study offers valuable insights into the intricate connection between innovation and financial performance.

For managers, the results emphasize the need for a more comprehensive approach to innovation management. The non-significant relationship between patents and EBIT implies that merely focusing on patents may not lead to superior financial performance. Managers should concentrate on fostering complementary resources and capabilities, including effective R&D management, marketing, and organizational learning, to capitalize on their patents and convert them into financial benefits (Grant, 1991, p. 133; Teece, 1986, p. 301). This perspective aligns with the resource-based view of the firm (Barney, 1991, p. 116) and the dynamic capabilities perspective (Teece et al., 1997, p. 516), which stress the necessity of continuous development and reconfiguration of a firm's resource base to adapt to evolving environments and maintain competitiveness.

Additionally, this study underscores the importance of considering alternative measures of innovation that more accurately reflect the innovative activities of firms and their impact on financial performance. Rather than solely concentrating on patents, managers should explore other facets of innovation, such as R&D expenditures, human capital, and implicit knowledge, which might be more pertinent in determining financial performance (Cohen & Levinthal, 1990, p. 132; Chen et al., 2006, p. 1337; Lev et al., 2009, p. 277). By adopting a holistic approach to measuring innovation, managers can attain a deeper understanding of their firm's performance drivers and make well-informed decisions.

For policymakers, the findings highlight the need to reevaluate the emphasis on patents as the primary measure of innovation. The non-significant relationship between patents and EBIT underlines the necessity of developing and utilizing more comprehensive measures of innovation when formulating and assessing innovation policies. Policymakers should consider a broader range of innovation indicators, such as R&D investments, intellectual property rights, and other intangible assets, when devising and implementing policies aimed at fostering innovation and economic growth (Chen et al., 2006, p. 1337; Lev et al., 2009, p. 277).

Furthermore, this study accentuates the significance of examining the role of industry-specific factors in shaping the relationship between patents and financial performance. Policymakers should consider the varying value of patents and their impact on firm performance across different industries (Lanjouw et al., 1998, p. 421; Ziedonis, 2004, p. 817). This may involve crafting tailored innovation policies that cater to the distinct needs and characteristics of various sectors, such as high entry barriers, strong appropriability conditions, or elevated levels of technological complexity (Levin et al., 1987, p. 830).

For investors, the findings offer valuable insights which can guide their investment decisions. The non-significant relationship between patents and EBIT suggests that investors should not solely depend on patent counts as an innovation proxy when evaluating investment prospects. Instead, investors should likewise consider a more extensive set of innovation indicators, such as R&D expenditures, intellectual property rights, and intangible assets, along with the firm's complementary resources and capabilities (Chen et al., 2006, p. 1337; Lev et al., 2009, p. 277; Teece, 1986, p. 297).

The results of the researchers' study align with those of Arora et al. (2013), who discovered that patents offer limited explanation for company performance when examining U.S. manufacturing firms. These findings also correspond with Bessen & Meurer's (2008, p. 3) research, which posits that the connection between patents and firm performance may rely on factors such as the legal environment and the effectiveness of the patent system. The authors' research builds upon their work by considering a broad array of control variables and employing advanced econometric methods.

In summary, this research adds to the literature on the relationship between patents and financial performance by presenting evidence that questions a simple, positive correlation between these variables. The findings hold critical practical implications for various stakeholders, underlining the necessity for a more sophisticated understanding of the innovation-performance relationship and the factors that shape it. By building upon these insights, future research can further enhance our comprehension of the complex interaction between innovation and firm performance.

8.3 Societal Implications

The swift advancement of AI carries far-reaching societal implications (Brynjolfsson & McAfee, 2014, p. 52). This study investigates the correlation between AI patenting and financial performance, underscoring the growing influence of AI in our world (Cockburn et al., 2018, p. 25).

AI's pervasive influence extends beyond economics, significantly impacting society's structure. Brynjolfsson and McAfee (2014, p. 75) point out how AI advancements permeate social interactions, thereby influencing various aspects of human life. The rising prevalence of AI technologies transforms societal norms, affecting how we communicate, work, learn, and entertain ourselves, and even altering our understanding of the world around us. While this research is primarily focused on the economic implications of AI patenting activities, it also worth mentioning the extensive role of AI in various societal contexts.

AI, once mostly associated with high-tech industries, now plays a crucial role in diverse sectors, including healthcare, education, transportation, and entertainment (Brynjolfsson & McAfee, 2014, p. 85). The widespread use and potential dependency on AI technologies necessitate a broader societal discussion about the role of AI in our lives. Simultaneously, the surge in AI technologies triggers a host of ethical dilemmas (Etzioni & Etzioni, 2017, p. 412). As AI technologies handle increasingly complex tasks, urgent ethical concerns related to privacy, accountability, and transparency come to the forefront (Bostrom & Yudkowsky, 2014, p. 316).

The data dependency of AI systems prompts questions about data collection, storage, and usage, leading to privacy concerns (Zuboff, 2019, p. 75). Furthermore, with AI gaining more autonomy, the necessity for establishing mechanisms for accountability when AI systems fail or cause harm arises (Russell et al., 2015, p. 111). AI also has a profound impact on labor markets, with automation posing threats to jobs, particularly those involving routine tasks (Arntz et al., 2016, p. 17). However, AI can also create new job opportunities, emphasizing the need for continuous skill development and lifelong learning to prepare individuals to navigate the evolving job landscape (Autor, 2015, p. 22).

This study indirectly contributes to these broader discussions. By examining AI patenting activities, the authors reflect on the accelerating pace of AI developments, which has implications far beyond the financial (Hall et al., 2001, p. 125). As AI's role in our lives continues to expand, it is crucial to foster open discussions about its ethical use, the establishment of comprehensive legal and policy frameworks, and strategies to mitigate its societal impacts (Bostrom & Yudkowsky, 2014, p. 322).

In conclusion, this study's findings extend beyond business administration and strategy, prompting considerations of wider societal and ethical implications of AI. This research promotes a deeper understanding of our AI-influenced future, facilitating a more informed societal discourse on responsible and ethical AI development and use.

9 Conclusion

The objective of this thesis has been to examine the impact of AI patents on company earnings across different industries and company sizes in a sample of European companies. The foundation of this analysis was the following research question: How does AI patent ownership affect company earnings, and is this relationship influenced by industry type and company size? Based on the research question and theoretical background, three hypotheses were developed. The main hypothesis of this thesis was, that AI patents owned by companies have a positive effect on company earnings. This was supplemented by two sub-hypotheses, concerning the impact of industry type and company size on this relationship.

To investigate the hypotheses, the researchers employed multiple linear regression analyses on a panel dataset consisting of company financial and AI patent data. Drawing inspiration from previous studies, the authors assessed how the relationship between AI patent ownership and company earnings varied across high-tech and low-tech industries and different company sizes.

The analysis in this paper led to the following conclusions regarding the three initial hypotheses:

Hypothesis 1: AI patents owned by companies have a positive effect on company's earnings.

Based on the findings, the researchers do not reject Hypothesis 1, as the results indicate a positive but statistically insignificant relationship between granted AI patents (lnPatent) and EBIT. This suggests that there may be a positive effect of AI patents on company earnings, but the analysis could not establish this relationship with statistical certainty.

Hypothesis 2: Patenting contributes more to a company's earnings in high-tech industries than in low-tech industries.

For Hypothesis 2, this study did not find enough evidence to support or reject this hypothesis. This inconclusiveness might stem from limitations in the dataset, or the methodology employed in the analysis. Further research could explore this question by incorporating more detailed data on various industries and conducting industry-specific examinations to ascertain the significance of industry type in the correlation between patenting and company earnings.

Hypothesis 3: The effect of owned patents on earnings is less pronounced the larger a company is.

This study could not conclusively support or reject Hypothesis 3, as the effect of company size on the link between patents and earnings remains unclear. While the results indicated a positive association between employee count and EBIT, the analysis did not offer adequate evidence to establish the interaction effect between company size and patent ownership. Additional research is required to delve into this aspect and gain a better comprehension of the role company size plays in the connection between patents and firm performance.

In summary, this research has shed light on the relationship between AI patents and financial performance, along with the potential impact of industry type and company size. Although the researchers could not definitively support or reject any of the initial hypotheses, their findings contribute to the ongoing scholarly discussion on patents' role in shaping company earnings. By building upon these findings and addressing the limitations faced in this study, future research can continue to enhance our understanding of the intricate relationship between innovation, patents, and firm performance.

10 Limitations

In this study, the researchers sought to examine the link between AI patents held by businesses, their earnings, the nature of the industries they operate in, and the size of these companies. However, several constraints may have impacted the researchers' capacity to derive conclusive findings from the data and propose directions for further investigation. In this section, the authors delve into the main limitations of their study, emphasizing problems related to data, methodological decisions, and external influences.

10.1 Data limitations

The study encountered a significant limitation in terms of data availability and quality. Due to data processing, as described in previous chapters, the original data set and the existing sample became smaller by several data points. The relatively small sample size might have reduced the statistical power of the analysis and hindered the detection of significant relationships among variables. Additionally, the data used in the analysis might not have been representative of the entire population of interest, potentially introducing biases in the results (Bryman & Bell, 2011, p. 619). The study also depended on secondary data sources, which could have caused issues with data accuracy and reliability. For example, AI patent and company earnings data may have suffered from reporting biases or measurement errors, impacting the analysis (Bryman & Bell, 2011, p. 619). Furthermore, the dataset lacked some potentially relevant variables, such as R&D expenditures, intellectual property rights, and other intangible assets, which have been identified as crucial factors for innovation (Chen et al., 2006, p. 1337; Lev et al., 2009, p. 277). The exclusion of these variables may have restricted the analysis' ability to thoroughly comprehend the investigated relationships.

The research employed a quantitative approach to examine the connection between AI patents, company earnings, industry type, and company size, enabling the analysis of large data quantities and pattern identification. However, this approach may have constrained the exploration of underlying mechanisms and contextual factors influencing these relationships (Creswell, 2009, p. 152). Additionally, the study used panel data, which, despite its advantages, presents certain limitations in capturing the dynamic nature of the relationships among patents, company earnings, industry type, and company size. One key limitation of panel data is the issue of missing data, which can lead to biased estimates and reduced efficiency in the analysis. In this study, missing data posed challenges in obtaining a complete picture of the relationships under investigation. Another limitation is the attrition problem, where units of observation drop out of the sample over time. Attrition can result in biased estimates if the reasons for dropout are related to the variables under investigation. The analysis also used various econometric techniques to address potential issues like heteroskedasticity and autocorrelation. Nevertheless, these methods may not have entirely resolved all methodological challenges, and residual issues could have remained in the analysis, such as omitted variable bias or multicollinearity, which might lead to erroneous conclusions (Wooldridge, 2016, p. 85).

The research centered on the relationship between AI patents, company earnings, while considering industry type and company size within a specific economic and institutional context, limiting the generalizability of the findings to other contexts or time periods. External factors, such as changes in patent laws, intellectual property rights enforcement, and national innovation policies, could affect the relationships under investigation (Bessen & Meurer, 2008, p. 3). Future studies should consider these external factors to offer a more comprehensive understanding of the factors influencing the relationships between patents, company earnings, industry type, and company size.

10.2 Statistical method limitations

The aim of the study is firstly to determine the relationship between AI patents granted and EBIT. Therefore, the difference between companies that file many patents and those that file only one or a few patents was analyzed. In this way, the researchers provided valuable insights into the relationship between patent activity and the financial performance of companies. However, this decision could have led to some bias in the results, as the relationship with companies that do not patent at all was not considered in this study. Future studies could therefore expand the sample by including companies that chose not to patent and analyzing their performance as well.

Second, the researchers decided to examine the relationship between AI patents and EBIT with a time lag of one year for both the control variables and the independent variable (patents). Although this is consistent with previous research, it was also done in part because of the short time period in which the topic of AI and patents emerged, making it difficult to analyze the impact over a longer period of time. Future research could therefore analyze the relationship with a different time lag (e.g., 2, 3, or 5 years) to account for potential fluctuations and maybe yield different results and insights into the long-term impact of AI patents on EBIT (Hausman et al. 1984, p. 923).

The researchers used multiple linear regression analysis as their main statistical method to analyze the relationship between the dependent variable and the independent variable. Even though multiple linear regression models are a popular and appropriate method to study the effects of different independent variables on a dependent variable (Wooldridge, 2016, p. 60), they have several limitations. One of the limitations is that the use of the model assumes a linear relationship between the independent variable and the dependent variable. This assumption is not always true and there may be a relationship between the variables at a more complex and non-linear level (Wooldridge, 2016, p. 64). The decision to use a linear model may limit the researchers' ability to fully capture the true underlying relationships between variables.

Furthermore, using multiple linear regression, one is anticipating that there is no strong correlation between the independent variables (multicollinearity). When multicollinearity is present, regression coefficient can be unstable and so the significance of single variables can be misleading (Wooldridge, 2016, p. 85). Even when the researchers use econometric techniques to address potential multicollinearity issues, there may still be some degree of multicollinearity in the analysis.

In addition, multiple linear regression relies on the assumption of homoskedasticity (Wooldridge, 2016, p. 45), meaning that the error terms' variance is constant across all independent variable levels. If this assumption is violated (i.e., heteroskedasticity is present), the standard errors and confidence intervals of the regression coefficients might be biased, leading to incorrect inferences (Wooldridge, 2016, p. 267). Despite the researchers' efforts to account for heteroskedasticity, residual issues might persist.

Lastly, the approach to analyzing Hypotheses 2 and 3 relied on sample splits by industry type and company size. However, it has been suggested that the use of moderator terms in the full sample model would be more appropriate given the linear moderation effect implied by Hypothesis 3. By including interaction terms (e.g., size measure * lnPatent) in the full sample model, the researchers could better understand the moderating effects of industry type and company size on the relationship between AI patents and company earnings (Wooldridge, 2016, p. 177-178). Future research should consider adopting this approach to provide a more nuanced understanding of the role of these contextual factors in shaping the relationship between AI patents and earnings.

In summary, while multiple linear regression provided valuable insights into the relationships between AI patents, company earnings, industry type, and company size, it is essential to recognize its limitations and consider alternative statistical methods in future research to further enhance the understanding of these relationships.

10.3 Future Research

This study has provided valuable insights into the relationship between AI patent ownership, company earnings, industry type, and company size. However, numerous opportunities for future research could further enhance our understanding of these relationships and their implications for innovation and financial performance. In this chapter, the authors propose potential avenues for future research, concentrating on data-related issues, methodological advancements, and the investigation of additional factors that may impact the relationships under study.

A critical direction for future research involves addressing the data-related limitations of this study. For instance, future studies could leverage larger and more diverse samples to bolster the generalizability and robustness of the findings. Incorporating other potentially relevant variables, such as R&D expenditures and other intellectual property rights into the analysis could offer a more in-depth understanding of the factors driving innovation and firm performance (Chen et al., 2006, p. 1337; Lev et al., 2009, p. 277). Future research could leverage methodological advancements to further analyze the relationships between AI patents, company earnings, industry type, and company size.

For instance, alternative statistical methods might be used to address certain limitations linked to multiple linear regression, such as the linear relationships assumption between variables and multicollinearity issues (Field, 2013, p. 324). Nonlinear regression models, like polynomial regression or spline regression, could be employed to investigate potential nonlinear relationships between variables (Field, 2013, p. 457). Additionally, methods like ridge regression or lasso regression could be implemented to tackle multicollinearity problems and enhance the stability of regression coefficients (Zou & Hastie, 2005, p. 308).

Given the hierarchical data nature (i.e., patents nested within companies), multilevel modeling or hierarchical linear modeling could be utilized to account for the data's nested structure and provide more accurate estimates of variable relationships (Raudenbush & Bryk, 2002, p. 3-4). Moreover, future research could explore machine learning techniques, such as random forests or neural networks, to predict company earnings based on AI patent ownership, industry type, and company size, potentially uncovering complex, nonlinear relationships and variable interactions (Breiman, 2001; Goodfellow et al., 2016).

Besides addressing data and methodological limitations, future research could also examine additional factors that may influence the relationships between AI patents, company earnings, industry type, and company size. For example, researchers could investigate institutional factors, like patent laws, intellectual property rights enforcement, and national innovation policies, that might shape the relationships under study (Bessen & Meurer, 2008, p. 3). Future studies could also analyze the impact of organizational factors, such as corporate culture, management practices, and employee skills, on the relationship between patent ownership and company earnings (Gibson & Birkinshaw, 2004, p. 209). Furthermore, the role of technological factors, like the pace of technological change and the degree of technological convergence, could be examined concerning the value of AI patents and their influence on company earnings (Ahuja & Lampert, 2001, p. 521). Lastly, future research could investigate the interplay between AI patents and other intellectual property forms, such as copyrights and trademarks, to offer a more nuanced understanding of intellectual property's role in driving innovation and financial performance (Hall et al., 2014, p. 418).

Another potential research direction is conducting international comparisons of the relationships between AI patents, company earnings, industry type, and company size. These comparisons could provide valuable insights into the generalizability of the findings across various countries and economic contexts. Researchers could examine whether the relationships under investigation are influenced by differences in national innovation systems, industrial structures, or cultural factors (Nelson, 1993, p. 347). Additionally, cross-country comparisons could help identify best practices and policy lessons that could be applied to enhance innovation and intellectual property policies' effectiveness in different countries. Researchers could explore government policies' role, such as R&D subsidies, tax incentives, and patent protection, in fostering innovation and improving the financial performance of companies with AI patents (Czarnitzki et al., 2011, p. 227).

In conclusion, this study has significantly contributed to understanding the relationships between AI patents, company earnings, industry type, and company size. However, there is still much to learn about these relationships and their implications for innovation and financial performance. By addressing this study's limitations and exploring additional factors, methodological advancements, and industry-specific issues, future research can build on these findings and provide a more comprehensive understanding of AI patents' role in driving innovation and financial performance.

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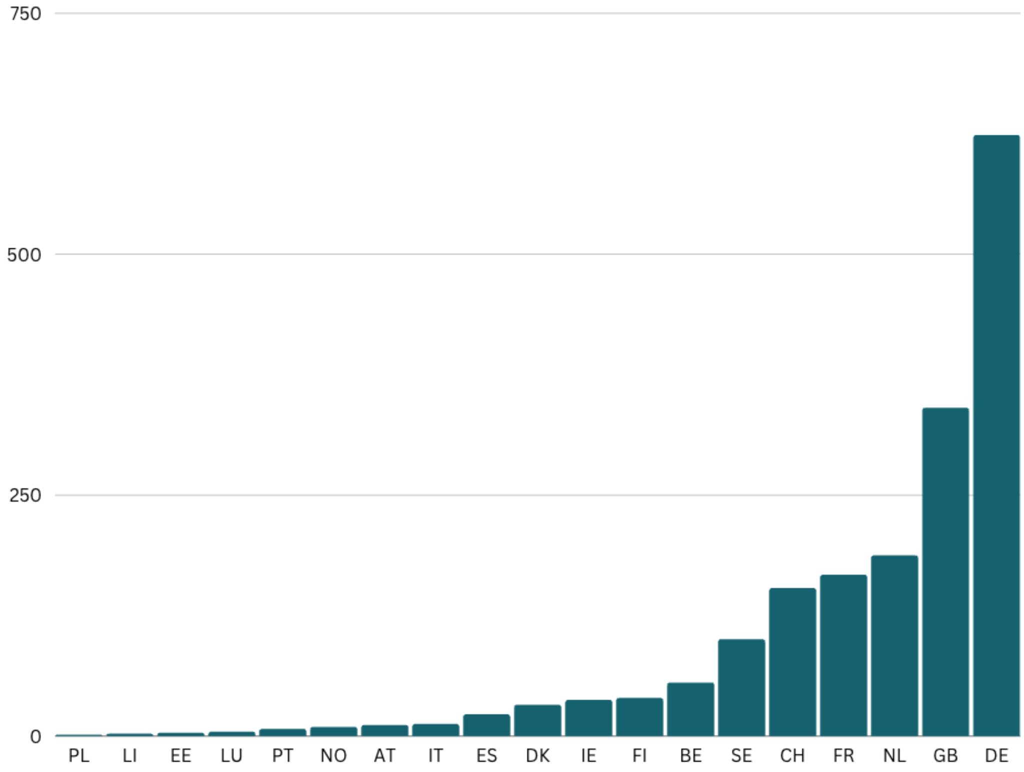
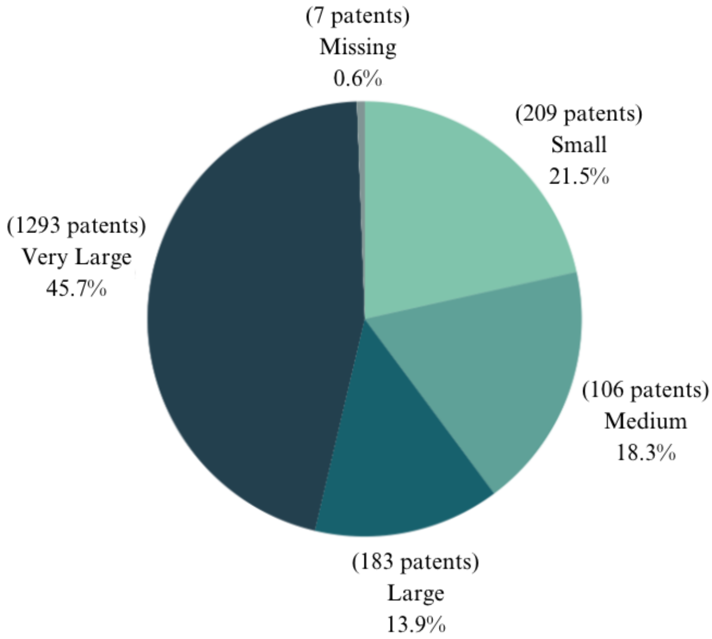
Appendix

Appendix 1 Distribution of Patents by Country



Appendix 2 Distribution of Company Size



Appendix 3 Stata Commands

```
/*
* Installs the asdoc program
ssc install asdoc

* Install winsorization program
ssc install winsor

* Install extremes program
ssc install extremes

* Install test for heteroskedasticity
ssc install xttest3

* Install package for wooldridge serial correlation test
net install st0039
*/

* Generate Variable Age
gen age= year-dateofincorporation

* Remove obs for negative Age values
drop if age<0

* Winsorize outliers from Variable Age
winsor age, gen(age_w) h(13)

* Winsorize outliers from Variable Ebit
winsor ebit, p(.01) gen(ebit_w)

* formats data as panel data with yearly intervalls
xtset id year, y

* encodes string data from categorical variables to numerical data

encode size, generate(numeric_size)

encode country, generate(numeric_country)

encode sector, generate(numeric_sector)

encode legalform, generate(numeric_legalform)

* Generate Dummy Variables for High/Low-Tech Sectors
recode numeric_sector (3 5 6 7 8 10 12 18=1)(1 2 4 9 11 13/17 19/ 21=0), generate(high_tech) test

```

```
recode numeric_sector (3 5 6 7 8 10 12 18=0)(1 2 4 9 11 13/17 19/ 21=1), generate(low_tech) test
* Correlation Matrix of key variables
asdoc pwcorr ebit_w patent totalassets longtermdebt profitmargin employees turnover age_w, sig star(5) append
* describes variables in data set
asdoc sum ebit_w patent totalassets longtermdebt profitmargin employees turnover age_w, label
* Distribution of company size
asdoc tab size, label
* Distribution of Industry Sector
asdoc tab numeric_sector [fweight=patent], m append
* Distribution of patents by
asdoc tab numeric_country [fweight=patent], m append
* Adding 1 to all Patent obs
gen patent1=patent+1
* Encoding missing observations of new Variable as 1
mvencode patent1, mv(1)
* Logarithmized Patent Variable
gen ln_patent=ln(patent1)
* Woldridge test doesn't allow lag indicator, thus creating new variable with lag
gen l_lnpatent=l.ln_patent
gen l_totalassets=l.totalassets
gen l_longermdebt=l.longtermdebt
gen l_profitmargin=l.profitmargin
gen l_turnover=l.turnover
gen l_employees=l.employees
gen l_age_w=l.age_w
* Simple linear regression with lag
asdoc reg ebit_w l.ln_patent, cluster(id) nest stat(r2_a) cnames( Simple) save(reg) replace
* Multiple linear regression incl. controll variables without lag
asdoc reg ebit_w ln_patent totalassets longtermdebt profitmargin turnover employees age_w, cluster(id) nest stat(r2_a) cnames( no_lag) save(reg) append
```

```
* Multiple linear regression incl. controll variables
and lag
asdoc reg ebit_w l.ln_patent l.totalassets
l.longtermdebt l.
profitmargin l.turnover l.employees l.age_w, cluster(id)
nest stat(r2_a) cnames(Multiple) save(reg) append

* Fixed Effects regression incl. controll variables
and lag
asdoc xtreg ebit_w l.ln_patent l.totalassets
l.longtermdebt l.
profitmargin l.turnover l.employees l.age_w, fe cluster(id)
nest stat(r2_a) cnames(Fixed) save(reg) append

* Modified Wald Test for heteroskedasticity of fx
regression
xttest3

* Wooldridge test for serial correlation
xtserial ebit_w l_lnpatent l_totalassets l_longermdebt
l_profitmargin l_turnover l_employees l_age_w

* Fixed Effects regression incl. controll variables,
lag, and clustered std errors
asdoc xtreg ebit_w l.ln_patent l.totalassets
l.longtermdebt l.
profitmargin l.turnover l.employees l.age_w, fe cluster(id)
nest stat(r2_a) cnames(Fixed_cluster) save(reg) append

* Joint F-test wether time fixed effects should be
used
asdoc xtreg ebit_w l.ln_patent l.totalassets
l.longtermdebt l.
profitmargin l.turnover l.employees l.age_w i.year, fe
cluster(id ) nest stat(r2_a) cnames(Time_Fixed) save(reg)
append

 testparm i.year

 * Hausman-Test to test whether Fixed or random
effects should be used

xtreg ebit_w l.ln_patent l.totalassets l.longtermdebt
l.
profitmargin l.turnover l.employees l.age_w, fe
estimates store fixed

xtreg ebit_w l.ln_patent l.totalassets l.longtermdebt
l.
profitmargin l.turnover l.employees l.age_w, re
estimates store random
```

```
hausman fixed random, sigmamore

/*
 * Hausman-Test to test whether Fixed or random effects should be used output

asdoc xtreg ebit_w l.ln_patent l.totalassets l.longtermdebt l.profitmargin l.turnover l.employees l.age_w, fe nest rep(p) stat(r2_a) cnames(Fixed Effects) replace
estimates store fixed

asdoc xtreg ebit_w l.ln_patent l.totalassets l.longtermdebt l.profitmargin l.turnover l.employees l.age_w, re nest rep(p) stat(r2_a) cnames(Random Effects) append
estimates store random

asdoc hausman fixed random, sigmamore nest append
*/

 * Fixed Effects regression incl. controll variables, lag, and clustered std errors for industry subset

 asdoc xtreg ebit_w l.ln_patent l.totalassets l.longtermdebt l. profitmargin l.turnover l.employees l.age_w, fe cluster(id) nest stat(r2_a) cnames(Full Sample) save(Industry) replace

 asdoc reg ebit_w l.ln_patent l.totalassets l.longtermdebt l. profitmargin l.turnover l.employees l.age_w if l.high_tech==1, cluster(id) nest stat(r2_a) cnames(High Tech) save(Industry) append

 asdoc xtreg ebit_w l.ln_patent l.totalassets l.longtermdebt l. profitmargin l.turnover l.employees l.age_w if l.high_tech==1, fe  cluster(id) nest stat(r2_a) cnames(High Tech Fixed) save( Industry) append

 asdoc reg ebit_w l.ln_patent l.totalassets l.longtermdebt l. profitmargin l.turnover l.employees l.age_w if l.low_tech==1, cluster(id) nest stat(r2_a) cnames(Low Tech) save(Industry) append

 asdoc xtreg ebit_w l.ln_patent l.totalassets l.longtermdebt l. profitmargin l.turnover l.employees l.age_w if l.low_tech==1, fe cluster(id) nest stat(r2_a) cnames(Low Tech Fixed) save(Industry)  append


 * Fixed Effects regression incl. controll variables, lag, and clustered std errors for size subset
```

```
asdoc xtreg ebit_w l.ln_patent l.totalassets
l.longtermdebt l.
profitmargin l.turnover l.employees l.age_w, fe cluster(id)
nest stat(r2_a) cnames(Full Sample) save(Size) replace

asdoc reg ebit_w l.ln_patent l.totalassets
l.longtermdebt l. profitmargin l.turnover l.employees
l.age_w if l.size_small==1 |
l.size_medium==1 | l.size_large==1, cluster(id) nest
stat(r2_a) cnames(Small-Large) save(Size) append

asdoc xtreg ebit_w l.ln_patent l.totalassets
l.longtermdebt l. profitmargin l.turnover l.employees
l.age_w if l.size_small==1 | l.size_medium==1 |
l.size_large==1, fe cluster(id) nest stat(r2_a )
cnames(Small-Large Fixed) save(Size) append

asdoc reg ebit_w l.ln_patent l.totalassets
l.longtermdebt l. profitmargin l.turnover l.employees
l.age_w if l.size_verylarge==
1, cluster(id) nest stat(r2_a) cnames(Very Large)
save(Size) append

asdoc xtreg ebit_w l.ln_patent l.totalassets
l.longtermdebt l. profitmargin l.turnover l.employees
l.age_w if l.size_verylarge== 1, fe cluster(id) nest
stat(r2_a) cnames(Very Large) save(Size) append
```

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