The Influence of AI-driven Disruptive Innovations on Incumbents' R&D Intensity Moderated by Industry Uncertainty: A Quantitative Analysis

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Master Thesis Strategic Management Consultancy

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June 13, 2025

Wordcount: 12,653

Abstract

This thesis investigates how AI-driven disruptive innovation affects incumbent firms' R&D intensity, and whether this relationship is moderated by industry uncertainty. Drawing on the established theory about disruptive innovations and strategic responses, the study conceptualizes AI-driven disruption as the average number of AI-related patents filed by new entrants within an industry. Using a panel dataset of publicly listed U.S. firms from 2015 to 2023, fixed-effects regression models are used to examine the influence of external AI patenting activity on internal R&D investment. The moderating role of industry uncertainty is examined along the three dimensions of dynamism, munificence, and complexity. The results show that there is no statistically significant relationship between AI-driven disruption and incumbent R&D intensity. Also, no significant moderation by the uncertainty dimensions is found. However, a number of internal firm characteristics, particularly R&D per employee, sales and net income, have a more substantial influence on R&D behavior. These findings challenge the assumption that external disruption signals affect innovation investment and instead suggest that firms' internal readiness and strategic interpretation are more important. This study contributes to a more nuanced understanding of how firms navigate AI-driven disruptive innovation and highlight the importance of internal capabilities in shaping strategic responses.

Management Summary

This thesis explores how incumbent firms respond to the rising impact of AI-driven disruptive innovations in the industry environment. As artificial intelligence continuously reshapes market dynamics and challenges established firms, there is a growing managerial interest in understanding how this type of disruption influences internal strategic innovation strategies, particularly investments in research and development (R&D). This study therefore focuses on whether and how AI-driven disruptive innovations affect the R&D intensity of incumbent firms, and whether this relationship is moderated by industry uncertainty. Industry uncertainty is examined through three dimensions, namely dynamism, munificence, and complexity.

The research applies a quantitative design using a panel dataset of U.S. publicly listed firms across multiple industries over the period between 2015 and 2023. AI-driven disruption was proxied by the average number of AI-related patents filed by disruptor firms in each industry and year. R&D intensity was measured as the ratio of R&D expenditure to sales for incumbent firms. Industry uncertainty variables were constructed from industry-level sales data and concentration measures.

The findings show that AI patent activity by disruptor firms does not have a statistically significant effect on the R&D intensity of incumbent firms. Furthermore, the dimensions of industry uncertainty do not significantly moderate this relationship. However, several internal firm-level characteristics, such as R&D per employee, sales, and net income, showed stronger associations with R&D investment behavior.

For managers, these findings suggest that external AI signals alone may not justify the need for increased R&D investment. Instead, firms should assess the threat of AI-driven disruptions in their own markets and industry context and decide whether specific features of

these innovations are relevant to their competitive positioning, customer needs, and technological capabilities. Accordingly, firms can make better informed decisions and avoid inefficient innovation investments. Additionally, the results from the study highlight the importance of internal innovation capabilities. Organizations with well-developed infrastructures, specialized teams, and sufficient resources seem to be more likely to pursue R&D investment. In conclusion, this study shows that adaptation to AI-driven disruption is not a universal or automatic response. Rather than reacting to external signals and industry activity, firms have to consider their internal readiness, strategic priorities, and interpretation of emerging threats when making innovation decisions.

Preface

This master thesis marks the completion of my master's in Strategic Management Consultancy at Tilburg University. The journey has been challenging at times but rewarding, as I have gained valuable insights into the evolving role of artificial intelligence as a driver of disruptive innovation in shaping strategic innovation responses.

I want to sincerely thank my supervisor, Dr. John Li, for his support, valuable feedback and academic guidance throughout this process.

I also want to thank my family, friends, and boyfriend for their encouragement and belief in me. Their patience and support have always been helpful and motivating throughout my educational career at Tilburg University. Lastly, I am proud of myself for conducting this final research over the past few months as a conclusion to my academic journey.

TABLE OF CONTENTS

Chapter 1 – Introduction

1.1 Problem Indication

In the current business environment, established firms (EF) are continuously challenged by disruptive business models due to ongoing technological development and digitalization (Madi-Odeh & Obeidat, 2024; Radnejad et al., 2022). These disruptive innovations simultaneously create growth opportunities in the industry, as well as threats to incumbent firms. In recent years, artificial intelligence (AI) has emerged as a powerful force driving disruptive innovation. AI is a general-purpose technology, which enables new entrants to achieve rapid growth and pose challenges to incumbent firms in data-rich, knowledge-intensive industries (Cockburn et al., 2018; Rammer et al., 2021). AI-driven innovations reshape competition by enhancing automation, decision-making, and predictive capabilities (Acemoglu & Restrepo 2018; Kaplan & Haenlein, 2019). Recent developments by OpenAI show how rapidly evolving AI capabilities, such as autonomous agents and generative tools, are transforming industries and intensify the pressure on firms to adapt (OpenAI, 2025). As a consequence, disruptors may bypass traditional learning curves and enter markets with lower costs or different value propositions (Babina et al., 2023). Confusion has occurred in the literature regarding what is included to be a disruptive innovation in terms of different types and characteristics, which can potentially lead to misunderstanding of the theory and hindrance of practical implications (Si & Chen, 2020). Without a proper specific definition of the concept this could result in disruptive innovation becoming another "business buzzword" (Nagy et al., 2016, p. 120). Particularly in the context of AI-driven disruption, traditional industry boundaries blur and the accelerated pace of change complicates theoretical classification, contributing to the ongoing lack of conceptual clarity in the literature (Grashof & Kopka, 2023).

The type of innovation that occurs more frequently is sustaining innovation, which implies improvements of products and services that have already been settled into the mainstream market (Christensen et al., 2018). This allows incumbent firms to achieve higher margins and profitability by selling more products "to their best existing customers" (p. 1047). However, with the emergence of AI, it is difficult for incumbents to sustain their competitive advantage through incremental improvements alone. In contrast, disruptive innovation could be described as a specific type of innovation or technological change, targeting a new customer base that deviates from the regular customer stream (Ben-Slimane et al., 2020; Radnejad et al., 2022). The concept evolved initially from the term disruptive technology by extending disruptions in the technology field to disruptions in other areas like products, services and business models (Shang et al., 2019; Si & Chen, 2020).

The process of defining the topic can be based on several perspectives, ranging from the sort of innovation activity to the evolving process, or from its effect in practice to its key characteristics (Si & Chen, 2020). Additionally, the focus could also be placed on identifying three innovation characteristics, namely radical functionality, discontinuous technical standards and ownership (Nagy et al., 2016). Following from these perspectives, two disruptive types result to be new market and low-end innovations (Christensen et al., 2018). Respectively these can be distinguished by their emphasis on the demand for new technology and the interest in existing technology for lower costs (Nagy et al., 2016). AI-driven innovations may fall into either category as outlined in disruption theory, but become especially powerful when combined with digital platforms, enabling disruptive firms to rapidly expand their reach and refine their offerings (Krakowski et al., 2023). The main goal of disruptive innovation is not necessarily focused on achieving the highest performing product, but rather on bringing new value propositions in lower performing products to the market that provide other benefits (Alpkan & Gemici, 2016). These types of innovation redefine the so-called 'rules of the game', resulting in the creation of new standards which may not align with the old status quo (Madi-Odeh & Obeidat, 2024). AI-driven innovation shifts the basis of competitive advantage away from traditional resources toward algorithmic capabilities and digital scalability (Babina et al., 2023; Rammer et al., 2021). This enhances competitive pressure, as firms with control over proprietary data can gain innovation advantages and establish high entry barriers in specific sectors (Cockburn et al., 2018).

Disruption materializes when emerging technologies match or exceed the performance levels of incumbents, altering customer preferences and market structures (Alpkan & Gemici, 2016). This is the point in the S-curve of innovation, after the introduction and transformation phases, in which the new technology crosses paths with the old one, as the innovation matures (Christensen, 1992; Si & Chen, 2020). In that case, the disruptors have found a gap in the market that convinces mainstream customers to switch to the newly introduced product (Ben-Slimane et al., 2020; Shang et al., 2019). The disruptiveness therefore lies in the process of changing the market (Si & Chen, 2020). Incumbent firms are not only challenged to remain competitive, but also to strategically reassess their allocation of innovation resources, particularly R&D investment, as a key response mechanism. AI disruptors may not outperform incumbents on product quality alone, as their data advantages and algorithmic improvements also create competitive pressure, encouraging incumbents to adapt their R&D strategies (Babina et al., 2023; Cockburn et al., 2018).

Since the base of competition changes, established firms might struggle competing with disruptive businesses as they are more conservative and attached to the old status quo than new players. Comparable to biological evolution, “organizations within the same population compete for similar resources or similar customers; some can adapt and survive, some cannot” (Alpkan & Gemici, 2016). Whether or not a company survives depends on the strategic actions they should take, which is a question that remains largely unanswered (Radnejad et al., 2022).

The chosen response strategy will be determined by whether it is a low-end or new-market disruption (Christensen et al., 2018). Since different types of innovations have different origins and competitive effects, they require different response approaches from incumbent firms (Markides, 2006). Innovations might be “disruptive to one firm but sustaining to another firm” and are thus relative (Christensen et al., 2018, p. 1050). Several response strategy types and forms exist, ranging from explorative to exploitative as well as adaptive or adoptive (Madi-Odeh & Obeidat, 2024; Schindler et al., 2024).

A lack of a holistic overview of disruption mechanisms and its features as well as the effect of various response strategies causes it to be difficult to determine what a company should do when disruptive innovation occurs (Hopp et al., 2018). Also, the dearth of predictive power due to the late identification of the occurring disruption makes it harder to apply an adequate strategy (Ben-Slimane et al., 2020). Predictive powers could lead to “recognition, strategy, and timing of disruptive innovation” helping managers to adjust their decisions accordingly and be aware of potential risks (Si & Chen, 2020). However, managers need to be informed about and trained in potential strategic responses, since otherwise their inertia and unpreparedness could hinder development (Ben-Slimane et al. 2020; Radnejad et al., 2022). The unique interpretation and perception of managers regarding the strategic environment influences their decision-making and is therefore significant (Madi-Odeh & Obeidat, 2024). The increasing awareness of the need to effectively deal with the complexity that disruptive innovation creates and its effect on market and firm outcomes, demands for an expansion of the research (Christensen et al., 2018). There is a growing call to better understand how firms can leverage AI-driven innovation to maintain or regain competitive advantage in response to evolving market dynamics (Grashof & Kopka, 2023; Rammer et al., 2021). Responding to this need, this thesis will extend the existing research by examining the evolving role of AI not just as a driver of disruption, but as a strategic enabler of innovation response, an area that is still underexplored in the literature (Cockburn et al., 2018).

1.2 Problem Statement

This research aims to address the gaps in understanding the interplay between AI-driven disruptive innovations and strategic responses by taking an empirical approach. A more nuanced conceptualization of the concept of disruptive innovation in the literature review will extend the clarification on the mechanisms and features. The focus in this research is on external, rather than internal, AI-driven disruptive innovations for firms, which will be represented by the average number of AI-related patents filed by disruptor firms in the same industry. Moreover, this study seeks to discover and analyze the types of strategic response strategies that can be employed by established firms and their potential impact on market and firm outcomes. Specifically, the empirical analysis will focus on R&D intensity as a strategic response from incumbent firms. Additionally, it will be interesting to see whether and in what way industry uncertainty, consisting of the dimensions of dynamism, munificence and complexity, moderates the relationship between AI-driven disruptive innovations and R&D behavior of incumbent firms. By addressing these elements, this study aims to contribute to the development of a comprehensive framework that enhances theoretical understanding and practical managerial implications in the current business environment.

The problem statement can thus be formulated as follows: How do AI-driven disruptive innovations influence R&D intensity, and how is this relationship moderated by industry uncertainty?

1.3 Research Questions

How can disruptive innovations be defined?

How do disruptive innovations differ in terms of the type (low-end or new market) and their effect?

How do established firms' strategic responses to disruptive innovations differ?

How does industry uncertainty moderate the relationship between disruptive innovations and strategic responses?

1.4 Thesis Structure

The rest of the thesis is structured as follows. Chapter 2 defines and discusses the different theoretical concepts from the established literature, leading to the development of the hypotheses. Chapter 3 will present the methodology and data used to do the empirical analysis. Chapter 4 will then show and evaluate the results found by the regression. Finally, Chapter 5 will discuss the findings, limitations and contributions of the study that follow from the results.

Chapter 2 – Theory

2.1 Conceptual Development

In order to understand the impact of AI-driven disruptive innovation on incumbent firms and their strategic response in the form of R&D investment, a theoretical foundation needs to be established. This chapter will explore the literature that has been established on the chosen variables. The first part will delve into the concept of disruptive innovation, discovering the different types of disruptions that exist and the various definitions that have arisen, and introduce artificial intelligence as a contemporary force that increasingly drives these disruptions. Secondly, it will be examined how incumbent firms can strategically respond to AI-driven disruptive innovation by distinguishing between different types of strategies. Finally, the concept of industry uncertainty is discussed to be able to further explore its role as a moderating factor in this study. By analyzing the different concepts and eventually linking them, hypotheses are formulated in Section 2.2 introducing the quantifiable measures as well.

2.1.1 Disruptive Innovation and Artificial Intelligence

The theory on disruptive innovation originated from the term "disruptive technology", referring to disruptions in the technology field that were "inferior in the main attributes that consumers of mainstream technology valued, but focused on some neglected attributes alternatively" (Si & Chen, 2020, p. 3). Christensen (1997) introduced this concept with his book Innovator's Dilemma after which the term has been used frequently in many different ways. Even though there is initial underperformance from disruptive technologies in the mainstream market, they eventually displace established technologies (Danneels, 2004). To include innovations in other areas than purely technology, the concept of disruptive technology evolved into the phenomenon of disruptive innovation (Markides, 2006; Si & Chen et al. 2020). However, both terms have been used interchangeably, which is not always correct (Cozzolino et al. 2018). As they "arise in different ways, have different competitive effects, and require different responses from incumbents" (p. 19), the distinguishment between different types of disruptions such as technological, business-model and product innovations should be clearly made (Markides, 2006).

A concise definition of disruptive innovation is needed to structure future research and prevent the phenomenon from becoming another *business buzzword* (Breyer-Maylander & Zerres, 2023; Nagy et al. 2016). This is especially true in rapidly evolving fields like AI, where definitional clarity is critical for both academic and managerial purposes (Kaplan & Haenlein, 2019). The initial theory defined it as a process by which a smaller, less resource-rich firm, successfully challenges incumbent firms by introducing a product starting in a niche market but eventually displacing dominant firms (Christensen et al., 2018). Antonio & Kanbach (2023) introduced a three-phase framework, highlighting how innovations progress from this niche introduction to a broader market impact and eventually industry transformation. The first phase looks at the disruptive susceptibility of the market, implying that the emergence of a disruptive innovation depends on multiple market factors and the present actors (Antonio & Kanbach, 2023). For example, when the risk of disruption is high, the appeal to mainstream customers is high and consequently the greater the opportunity is to conquer market share (Adner, 2002). This thus involves market factors like customer readiness or market gaps as well as incumbent firms recognizing the threat of disruption instead of ignoring or dismissing them initially.

Artificial intelligence has emerged as a contemporary driver of this process. It is increasingly viewed as a general-purpose technology that stimulates innovation across sectors and serves as an important source of disruptive potential (Cockburn et al., 2018). Artificial intelligence (AI) can be 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" (Kaplan & Haenlein, 2019, p. 5). It refers to methods that enable machines to perform tasks and make intelligent decisions based on environmental input (Cockburn et al., 2018). Human skills like perception, cognition, and problem-solving enable the automation of processes, improvement of operational quality and enhancement of products and services through self-learning algorithms (Rammer et al., 2021). AI-driven disruptors do thus not rely on traditional performance improvements, rather they leverage digital scalability, access to proprietary data, and algorithmic optimization to challenge incumbents in novel ways.

The disruptive innovations that emerge as a result of the market factors in the first phase can be categorized into several types. Distinguishing between these types based on the type of innovation activities can aid in defining the phenomenon of disruptive innovation (Si & Chen, 2020). Christensen identified two types of disruptions: new market and low-end innovations (Christensen et al., 2018). New market innovations imply the creation of "new demand for a new technology, resulting in consumers demanding this new product" (Nagy et al., 2016, p. 120). This type serves customers in markets that did not exist before and are created as a consequence of the innovation (Antonio & Kanbach, 2023). Low-end innovations on the other hand "provide similar characteristics to existing technologies but cost substantially less" (Nagy et al., 2016, p. 120). This type is especially focused on serving price-sensitive customers in established markets (Antonio & Kanbach, 2023). AI-driven disruptions sometimes follow this low-end route when they begin in niche markets, such as automated customer service, diagnostics or analytics, but then expand upwards due to low marginal costs and learning-based improvements (Cockburn et al., 2018; Rammer et al., 2021). Markides (2006) proposed three other categories to distinguish between different types of disruptions: technological, business-model and product innovations. These respectively introduce new technologies, new business models in existing businesses and new products. Despite the fact that these three types all intrude with the current market affairs, the kinds of markets that are created and the speed at which this happens, differ from one type to the other (Markides, 2006).

The second phase considers the further emergence and diffusion of disruptive innovations. Acceleration in the form of performance growth and market penetration are the key elements of this stage (Antonio & Kanbach, 2023). The disruptive innovation gradually improves according to the mainstream performance metrics and is increasingly adopted among mainstream customers (Ben-Slimane et al., 2020; Schindler et al., 2024). Nagy et al. (2016) discuss three innovation characteristics that have an influence on the performance metrics or consumer expectations of a market. They state that a sustaining innovation can flow from functionality, technical standards, and ownership with which an organization is familiar. Contrarily, for a disruptive innovation these three characteristics are unfamiliar to the organization. The unfamiliarity demands firms to change the way of working and perhaps the way they approach the market and their customers (Nagy et al., 2016). For AI-driven disruption specifically, successful adoption requires not only technical investment, but also organizational restructuring, reskilling of the workforce, and new data management capabilities (Rammer et al., 2021).

In the final phase of the framework, the performance of the disruptive innovation intersects with the mainstream market demands, and the actual disruption happens (Alpkan & Gemici, 2016). Schmidt & Druehl (2008) note that disruptions also cause financial and reputational changes. The mainstream market gets dominated by the new disruptive innovation, possibly resulting in the displacement of incumbents (Ben-Slimane et al., 2020). Incumbents can decide on how to respond, which will be discussed later in this chapter. However, the effect in practice is also one element to base the definition of disruptive innovations on. Si & Chen (2020) mention a number of papers that emphasize the end result of a disruption to be the core component that defines something to be disruptive. This end result can be recognized in various ways, from disrupting the established trajectory, reshaping the meaning of performance or even changing financial indicators like stock prices (Si & Chen, 2020). To better capture the timing of AI-disruptive transformations, Chen et al. (2015) propose a timing framework distinguishing between ‘D-day’ (the date of disruption initiation) and ‘V-day’ (the date of value realization). This distinction is especially relevant for AI-driven innovation, for which performance gains and competitive effects may materialize only after a longer phase of gradual improvement and diffusion. Consequently, incumbents may not observe such transition until market share has already begun to shift, or new standards have been established.

To further enable the creation of a concise definition, three additional elements should be considered. Firstly, it should be acknowledged that disruptive innovation is not just a mere outcome, it is a progressive process (Si & Chen, 2020). Comparing it to the S-curve of innovation it can be noted that the inferiority in performance of the disruptive innovations in combination with gradually attracting mainstream customers who initially ignore the newly introduced products or services, support this characteristic (Christensen et al., 1992). The process goes through the different growth and maturing stages that are represented in the S-curve (Christensen et al., 1992). Eventually when the new S-curve of disruptors intersects with the curve from incumbent firms, superior performance can be reached, which could result in the new technology dominating the market (Adner & Kapoor, 2015). Moreover, if an innovation is assessed based on its effect it is hard to determine whether it is disruptive or not. The relative nature of the disruption causes an innovation to potentially be beneficial to one firm whilst being detrimental to another (Christensen, 2006). Additionally, Christensen suggests that regarding disruptive innovation, the challenge is related more to marketing than it is about the actual technology (Corsi & Di Minin, 2014). Building capabilities to forecast market trends or attitudes can be helpful in handling and addressing the needs in the changing technology business landscape (Charitou & Markides, 2003; Corsi & Di Minin, 2014). Furthermore, in the literature there is disagreement about what the key characteristics of disruptive innovations are. The most commonly mentioned characteristics are initial inferiority in mainstream attributes

(Corsi & Di Minin, 2014), provision of a new value proposition (Alpkan & Gemici, 2016; Ben-Slimane et al., 2020), a low-margin and small-scale business model (Si & Chen, 2020), lower prices compared to existing products or services (Antonio & Kanbach, 2023; Nagy et al., 2016) and penetration from a niche market slowly moving to mainstream markets displacing incumbents (Ben-Slimane et al., 2020; Christensen et al., 2018; Cozzolino et al., 2018). Si & Chen (2020) formulated the following definition based on these characteristics: *An innovation process in which technologies, products or services are initially inferior than those provided by incumbents in the attributes that mainstream consumers value, but these technologies, products or services can attract and satisfy the consumers in low-end or new markets with advantages in performance attributes (such as being cheap, simple, or convenient) that these consumers value but which at the same time are neglected by mainstream markets. Overtime, through incremental improvement of technology or process, a disruptive innovation gradually satisfies the needs of mainstream consumers, so as to attain certain market share from or even replace incumbents in mainstream markets* (p. 6).

In the context of disruptive innovation, AI is not just an enabling tool but a transformative force that changes the basis of competition by integrating algorithmic intelligence into products, services, and processes (Cockburn et al., 2018; Rammer et al., 2021). AI is increasingly associated with disruptive change, particularly when it challenges incumbent firms through new business models or cost-efficient solutions (Babina et al., 2023). Accordingly, this study conceptualizes AI as an external technological force that drives disruptive innovation.

2.1.2 Strategic Responses

As the second phase of the three-phase framework evolves, incumbents start to realize conditions are effectively changing because of the disruptive innovation and they might have to respond (Antonio & Kanbach, 2023). Numerous types of strategic responses exist as firms can take on different attitudes to deal with the changed rules of the game (Madi-Odeh & Obeidat, 2024). Charitou & Markides (2003) propose five different types of responses: focus on and invest in the traditional business, ignore the innovation, attack back, adopt the innovation by playing both games at once, or embrace the innovation completely and scale it up. These response types reflect the varying degrees to which incumbent firms recognize and address the threat posed by disruptive innovations. Such strategic choices are complex in the case of AI-driven disruption, as AI often affects the core capabilities and changes the pace and logic of innovation (Cockburn et al., 2018). Since initially disruptive innovations do not apply to the mainstream market, incumbents could consider them to still be irrelevant and might ignore them. Non-responses as a result of irrelevance can have several causes, both internally and externally. Regarding internal motives, incumbents could prefer to allocate their resources to other purposes for example when they do not perceive the disruptive innovation to be a big threat (Yu & Hang, 2010). Also, they could suffer from organizational inertia in which case firms might be so embedded in their traditional way of doing business that it can be hard to adjust and in this initial stage it might not seem necessary to change (Radnejad et al., 2022). On the other hand, the disruptive innovation could have a quick growth rate, and firms could consider it to not be worth the effort (Markides, 2006). Lastly, firms might not recognize the disruptive nature of a disruptive innovation in time when initially underestimating the potential threat (Schmidt & Druehl, 2008). Such delayed recognition is particularly risky in fast-evolving areas such as AI, where early adopters may rapidly reshape industry standards and consumer expectations (Babina et al., 2023).

A second response strategy is to focus on and invest in one’s own traditional business. Firms will then try to make their traditional product more attractive in order to stay competitive (Charitou & Markides, 2003). By changing the value proposition of the current market, incumbents try to prevent mainstream customers from being captured by the disruption (Alpkan

& Gemici, 2016). For example, AI-enabled enhancements to existing products, such as predictive analytics or automation layers, can be positioned as differentiating aspects to protect market share of incumbents (Kaplan & Haenlein, 2019). The third response could be to attack back and “disrupt the disruption” (Charitou & Markides, 2003, p. 60). Taking an aggressive stance by introducing new innovations or improvements can serve as a counter-reaction to the disruptive innovation. In AI-intensive sectors, this might require firms to strengthen their internal innovation capabilities, develop digital competencies, and adopt a proactive attitude towards technological change (Grashof & Kopka, 2023). Another option is to adopt the disruptive innovation internally while also continuing the traditional business and thus “playing both games at once” (Charitou & Markides, 2003, p. 60). The term ambidexterity describes this process, as it enables firms to simultaneously explore and exploit sustaining as well as disruptive innovations (Schindler et al., 2024). Numerous papers suggest the establishment of a separate autonomous business unit to be a good solution to deal with disruptive innovation while continuing the traditional business activities (Alpkan & Gemici, 2016; Corsi & Di Minin, 2014). The creation of a separate unit allows for the balance between both sustaining and disruptive innovation activities through an organizational structure that can adapt to the changing market as well as leverage existing capabilities (Schindler et al., 2024). AI adoption can demand this ambidextrous approach, with firms maintaining legacy operations while also creating separate digital or data science units to experiment with machine learning tools or data-driven business models (Krakowski et al., 2023; Lee et al., 2022). The final option that Charitou & Markides (2003) propose is to quit the traditional business activities and instead embrace the disruption by scaling up on it. As a result, the incumbent firm becomes direct competition for the original disruptor again (Alpkan & Gemici, 2016). In AI contexts, such a shift could involve changing from physical product offerings to algorithmic services or adopting data-driven business models in which value is generated through interactions between users, algorithms, and digital infrastructure (Cockburn et al., 2018; Rammer et al., 2021). This type of transformation typically requires a substantial reallocation of resources and exposes firms to increased strategic and operational risks.

The different strategic responses discussed in this section can result in varying levels of R&D investment. Firms that choose to attack back or embrace the disruption are likely to increase their R&D intensity to accelerate innovation or scale up new technologies. In contrast, firms that choose to ignore the disruption or maintain their status quo may keep R&D investment flat or reallocate resources defensively. Responding effectively in the context of AI requires internal investments in R&D capabilities, data infrastructure, and technical expertise (Cockburn et al., 2018; Hall & Lerner, 2010; Rammer et al., 2021). R&D intensity therefore serves as a practical indicator of how firms translate their strategic decision-making into innovation efforts.

2.1.3 Industry Uncertainty

This study will consider industry uncertainty as a moderating variable. To analyze industry conditions three key dimensions of the broader concept of environmental uncertainty will be examined: dynamism, complexity and munificence.

The first dimension dynamism focuses on the stability of an organizational environment (Dess & Beard, 1984). In stable environments, firms can focus on the current state of affairs and maintain their market position, whereas rapid environments require firms to be quick and responsive to changes in order to remain their competitiveness (Dess & Beard, 1984). High volatility and unpredictability in an environment can lead to difficulties in predicting changes and demands in a market (Anderson & Tushman, 2001; Harrington & Kendall, 2005). Rapid changes may require innovation and adaptation (Chen et al., 2017). However, unpredictable environments may also result in firms acting with more caution (Keats & Hitt, 1988). AI-driven disruption may intensify environmental dynamism due to rapid evolution and changing customer expectations.

The second dimension is munificence, which refers to the abundance of resources and opportunities (Chen et al., 2017; Rueda-Manzanares et al., 2008). The excessive availability of resources fosters and facilitates organizational growth, opportunities for expansion and survival (Anderson & Tushman, 2001; Keats & Hitt, 1998). In high munificent contexts more aggressive growth strategies could be pursued, like expansion and diversification, whereas less munificent contexts may demand more conservative strategies that focus on cost control and efficient resource allocation (Dess & Beard, 1984).

The final dimension that will be considered regarding uncertainty is complexity, which describes the heterogeneity and concentration of environmental elements that an organization deals with in its environment (Keats & Hitt, 1988). The high degree of interconnectedness involves numerous interdependencies and relevant actors and variables (Anderson & Tushman, 2001). With high complexity there is a greater variety of stakeholders that organizations must manage (Dess & Beard, 1984), as well as a greater variety of challenges and factors that firms must navigate within the operational environment (Chen et al., 2017). AI technologies possibly contribute to increased industry complexity by introducing technological uncertainty, ethical challenges, and interdependencies across data-driven ecosystems. A more heterogenous environment encourages innovation in order to enable firms to adapt to the market demands (Miller & Friesen, 1983). Flexibility and adaptability can therefore be prioritized in their operations (Dess & Beard, 1984). By developing unique capabilities and strategies firms could exploit opportunities instead of merely react to challenges (Aragon-Correa & Sharma, 2003).

2.2 Hypothesis Development

After establishing the theoretical foundations of disruptive innovation, strategic responses and industry uncertainty, this section will formulate the hypotheses that define the relationships between the variables. While the concepts of disruptive innovation and strategic responses are broad in scope, this thesis narrows its empirical focus by operationalizing them through AI-related patent activity and firm-level R&D intensity, respectively. These proxies are used in prior research, as AI patent activity reflects the emergence and diffusion of disruptive technologies (Cockburn et al., 2018), and R&D intensity captures the strategic allocation of resources regarding innovation and adaptation (Rammer et al., 2021).

2.2.1 AI-patenting activity and R&D intensity

The products and services introduced through disruptive innovations often show initial underperformance in mainstream markets but, after gradual improvement, gain attention and may ultimately displace incumbent firms (Christensen, 1997; Si & Chen, 2020). The three-phase framework proposed by Antonio and Kanbach (2023) highlights the evolution of disruptive innovations from niche markets to mainstream dominance. To empirically capture AI-driven disruptive innovation in a quantifiable and observable manner, AI-related patenting activity by disruptor firms will be used as a proxy in this thesis. Patent filings, particularly in the field of AI, are indicative of early-stage, potentially transformative technologies and therefore serve as a valid signal of disruptive innovation in progress (Cockburn et al., 2018). Artificial intelligence represents a key element of contemporary technological development, reshaping traditional business models and competitive dynamics (Fenwick et al., 2018). In the transition phase of Antonio and Kanbach’s framework (2023), incumbents face critical strategic decisions in response to such disruptions. Charitou and Markides (2003) introduced five categories of response strategies: ignoring the innovation, reinforcing the traditional business, disrupting the disruptor, adopting the innovation while maintaining current operations, or fully embracing the disruption. The extent to which incumbents recognize the threat and respond to the disruptive innovation determines the effectiveness of their strategic choices. Failing to acknowledge or underestimating the potential disruption may result in the displacement of incumbent firms (Schmidt & Druehl, 2008). Conversely, firms that proactively respond, by investing in innovation or adopting ambidextrous strategies, may retain their market position (Schindler et al., 2024). Among the possible responses, investment in research and development can be considered both defensive and adaptive. Incumbents may use this strategy to enhance technological capabilities, explore alternative paths or compete with disruptive innovations. Lee et al. (2022) argue how "R&D is fundamental to the adoption and utilization of new technologies" (p. 3). To analyze and exploit external circumstances effectively, it is necessary to enhance internal knowledge through investment in internal R&D. The theory of *absorptive capacity* by Cohen and Levinthal (1990) supports this view by highlighting the importance of prior related knowledge within the firm. This prior knowledge enhances a firm's absorptive capacity, defined as the "ability to recognize the value of new information, assimilate it, and apply it to commercial ends" (p. 128). Therefore, strengthening internal R&D capabilities is essential for firms to develop the absorptive capacity needed to effectively identify, incorporate and capitalize on technological innovations. Consequently, to test the relationship between AI-driven disruptive pressure and strategic adaptation, the following hypothesis is derived:

H1: AI-patenting activity by disruptor firms in an industry positively influences the R&D intensity of incumbent firms.

2.2.2 The Moderating Role of Industry Uncertainty

Industry uncertainty plays a critical role in shaping how incumbent firms respond to external AI-driven disruption. Building on the environmental dimensions of Dess and Beard (1984), this study focuses on three distinct moderators, namely dynamism, munificence and complexity, as they may affect how strongly firms react to AI-driven innovations with increased

R&D investment. By introducing these moderators, the analysis acknowledges that a particular AI signal may provoke different strategic investment behaviors depending on the environmental conditions incumbent firms face.

Dynamism refers to the rate and unpredictability of change within an industry, possibly hindering incumbent firms to adequately adapt to market demands (Anderson & Tushman, 2001). In highly dynamic environments, characterized for instance by rapid technological evolution, the pressure to respond rapidly to emerging disruptions is intensified for firms. The urgency enhances the perceived importance of AI patent activity, making it more likely that firms interpret such signals as strategic threats. In such conditions, organizational flexibility becomes essential, as rigid structures or delayed responses may result in lost competitive ground (Eisenhardt & Martin, 2000; Teece et al., 1997). According to Teece's (2007) dynamic capabilities framework, firms that can rapidly adapt and reallocate resources are better positioned to respond with innovation-driven strategies like increased R&D investment. Additionally, aligning R&D with AI adoption intensity can enable firms to gain greater value from such technologies, especially in fast-evolving industries (Lee et al., 2022). In contrast, in more stable industries, incumbents may perceive less urgency which could potentially delay R&D response. Therefore, the following hypothesis is proposed:

H2: Industry dynamism positively moderates the relationship between disruptor AI patenting activity and incumbent R&D intensity.

Munificence expresses the abundant availability of resources and opportunities in an industry, influencing how firms respond to external AI-driven disruption. In resource-rich environments, firms usually enjoy greater financial and operational flexibility, enabling them to apply proactive innovation strategies like increased R&D investments (Chen et al., 2017; Rueda-Manzanares et al., 2008). Firms embedded in munificent contexts are more likely to possess surplus resources, enabling them to acquire, combine and redistribute assets in response to significant threats (Rueda-Manzanares et al., 2008). This is relevant for AI-driven disruption, for which firms must invest in various capabilities such as a skilled workforce, infrastructure, and experimentation to compete effectively (Grashof & Kopka, 2023; Rammer et al., 2021). Aragon-Correa and Sharma (2003) argue that firms with access to plentiful resources are more likely to engage in proactive, rather than reactive, responses to external disruptive pressures. Moreover, munificence can facilitate the development of absorptive capacity by allowing for sustained investment in internal R&D systems (Cohen & Levinthal, 1990). In contrast, resource-scarce environments might force firms into more conservative cost-cutting strategies, limiting their ability to respond to emerging AI disruptions through R&D investments and innovation. Therefore, this second moderator develops the following hypothesis:

H3: Industry munificence positively moderates the relationship between disruptor AI patenting activity and incumbent R&D intensity.

The final dimension complexity refers to the heterogeneity and concentration of environmental elements in an industry, including a variety of technologies, stakeholders, and market demands (Miller & Friesen, 1983). High industry complexity can complicate strategic decision-making, as it is more difficult to identify disruptions due to a wide range of sometimes conflicting signals. Consequently, the challenge of interpreting the relevance and urgency of AI-driven disruption is amplified. Prior research suggests that such conditions can impair firms' ability to accurately assess environmental change, increasing the risk of misinterpretation or delayed strategic response (Miller & Friesen, 1983; Simon, 1991). Simon (1991) further explains that under conditions of bounded rationality, cognitive limitations constrain how decision-makers process complex information, thereby reducing their strategic clarity. Furthermore, complexity may introduce coordination costs, as large incumbent firms might struggle to reach internal agreement on decisions or reallocate resources quickly enough to initiate an effective R&D response. Cockburn et al. (2018) also suggest that the general-purpose nature of AI introduces additional complexity in understanding and managing innovation, particularly given its broad applicability and the interplay of multiple overlapping technologies. This may challenge firms' ability to evaluate the significance of innovations along the incremental-disruptive spectrum. Such decision-making constraints may hinder firms' ability to respond swiftly and strategically through targeted R&D investments. Therefore, firms operating in highly complex industries may be less likely to respond to external AI patent activity with immediate R&D investments. In contrast, less complex environments may allow for quicker, more focused responses due to more transparent information and more predictable stakeholder dynamics. Thus, the final hypothesis is:

H4: Industry complexity (as measured by the Herfindahl index) negatively moderates the relationship between disruptor AI patenting activity and incumbent R&D intensity.

Figure 1 presents the conceptual model that is derived from the theoretical framework and hypotheses as outlined above.

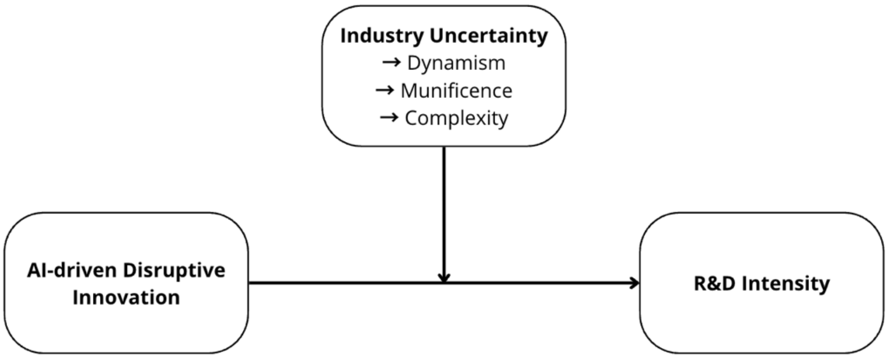

Figure 1: Conceptual Model

Chapter 3 – Methods

Due to the explanatory nature of the thesis, the research strategy of archival research was applied using quantitative secondary panel data. This chapter will explore the methodology employed in order to test the formulated hypotheses and find an answer to the problem statement, by describing the sample and setting, the measurements used and the empirical analysis that is performed.

3.1 Sample and setting

3.1.1 Sample composition

The sample was selected based on a variety of criteria for inclusion. A non-probability sampling method was employed to gather the sample, based on data availability and relevance, with the focus on AI activity and the associated strategic data. The geographical scope of the sample is North America, specifically the United States, for the reason that the U.S. is a global leader in AI innovation with a significant share in AI-related patents and the presence of headquarters of many leading firms (Google, IBM). The high availability of data on patents, as well as on financial and strategic disclosures, combined with the competitive environment in the U.S. makes this geographical region well-suited for this research. Secondly, the time horizon for the sample was chosen to cover the period from 2015 to 2023. Around 2015, businesses began to integrate AI into the business landscape instead of using it for experimental research only (Cockburn et al., 2018). The period aligns with data availability and quality, and also provides a large enough time frame to allow for changes in AI-driven disruption behavior of firms. Third, the sample includes firms from various industries, especially those leaning toward high-tech and manufacturing sectors focused on software/IT services, electronics and instrumentation. Only publicly listed firms are included to ensure greater availability and reliability of the included data. Finally, rows were deleted from the sample with a negative or zero amount of R&D intensity, with a negative net income, and if there were any missing values in the relevant variables of the regression.

3.1.2 Data

Patent data for this research was obtained from the Artificial Intelligence Patent Dataset (AIPD), which is a structured dataset derived from the U.S. Patent and Trademark Office (USPTO). The raw data included publication year, patent classification, firm names and the AI subdomain. The average annual number of AI-related patents as the independent variable serves as a proxy for AI-driven disruptive innovation. Firm-level financial and organizational data were retrieved from the Compustat North America database via WRDS. The dataset includes information on firm characteristics such as R&D expenditures, sales, assets, employment, and capital investments. These variables were used to construct the dependent variable (R&D intensity), several control variables, and the industry-level moderators (dynamism, munificence, and complexity). Firms were matched by *gvkey,* and the data were structured as a balanced panel covering the period from 2015 to 2023. The initial raw dataset consisted of 28,395 observations. After the cleaning process, removing incomplete or irrelevant data and narrowing down to fit the focus of this thesis, the final sample resulted to consist of 2,255 observations. As part of the regression preparation process, continuous variables were winsorized at the 1st and 99th percentiles to reduce the influence of extreme outliers without deleting data. Particularly the highly skewed financial metrics such as capital expenditures and sales could otherwise distort the regression estimates.

3.2 Measurements

3.2.1 Dependent variable: R&D intensity

As a proxy for the chosen type of strategic response, this research will use the research and development (R&D) intensity of incumbent firms. The variable captures the extent of strategic innovation investment by incumbent firms, as a reaction to the introduction of AI-related patent filings by disrupting firms. It was calculated as the ratio of research and development expenditure to sales and retrieved from the Compustat database. As R&D intensity is a ratio variable, its values are bounded between 0 and 1. A small number of firm-year observations that contained implausible or erroneous values outside the expected range were removed during the data cleaning process. This operationalization followed practices in established innovation studies, where R&D intensity is frequently used as a proxy for firm-level innovation behavior (Cohen & Levin, 1989; Hall & Lerner, 2010).

3.2.2 Independent variable: AI-related patent filings

The main independent variable in this study captures the external technological disruption that a firm is exposed to in its associated industry. The variable is constructed as the natural logarithm of the average number of AI-related patents filed by disruptor firms within the same industry and year. To identify "disruptor" firms, the dataset has made a distinction for firms that have a firm-level AI patenting age of one year or less. These disruptor firms are assumed to be the sources of the technological interference and competitive pressure in the external environment. The initial construction of this variable started with matching the AIPD patent dataset with the Compustat firms by assignee name. The identified disruptor firms were filtered from the dataset to be included in the formation of the independent variable. The AI-related patent counts of these disruptors were aggregated at the industry-year level, after which the mean number of patents per industry-year was then calculated. Patent count data is highly skewed and often includes zeros, so therefore a log transformation was applied with a +1 offset. Consequently, the final variable does not just capture the presence of AI-driven disruption, rather it captures the intensity of innovation coming from new AI entrants that incumbent firms potentially have to respond to. This approach is consistent with previous studies that link AI-driven activity, particularly from new entrants to external technological pressure and disruptive innovation in industries (Acemoglu & Restrepo, 2018; Bessen, 2006).

3.2.3 Moderators: Dynamism, munificence, complexity

To include the effect of external environmental conditions on the relationship between AI disruption and strategic behavior of incumbents, three industry-level moderators were introduced. Representing the key dimensions of industry uncertainty, these three moderators are dynamism, munificence and complexity. Dynamism is measured as the standard deviation of industry sales over a five-year regression window, capturing the level of volatility and unpredictability in the firm's external environment. This operationalization follows established measures of dynamism as sales volatility over time (Dess & Beard, 1984; Keats & Hitt, 1988) and conceptually aligns with more recent treatments of environmental uncertainty (McKelvie et al., 2009). Higher dynamism can demand more frequent and substantial changes, which may necessitate adaptive strategies for firms such as increased R&D investment.

The second moderator munificence is calculated as the slope coefficient of a linear regression of industry sales on time over five years, following the empirical approach of Keats and Hitt (1988). This captures the availability of external resources, which conceptually reflects the environmental richness and opportunity structures as discussed by Castrogiovanni (1991). A positive slope coefficient is indicative of an expanding industry context with growing opportunities, while a negative slope reflects industry contraction.

Finally, complexity is proxied by the Herfindahl-Hirschman Index (HH) of industry sales. Higher values indicate more concentrated markets and potentially a more complex strategic landscape. This measure accounts for the number of competitors and dominance of firms in the industry, which shape the competitive intensity and strategic complexity in the industry. The conceptualization aligns with prior studies linking market structure to firms' ability to interpret and respond to environmental challenges (Dess & Beard, 1984) and is empirically supported in recent innovation studies (Anderson & Tushman, 2001). All three variables are time-varying and calculated at the industry-year level, enabling context-sensitive analysis of how environmental conditions shape incumbent firms' strategic responses.

3.2.4 Control variables

This research will include multiple control variables to control for a number of factors that might affect the relationship between AI-driven disruption and R&D intensity. Specifically, most of the controls account for internal firm characteristics that might influence R&D investment independently of external AI-driven disruption. Net income is included to represent the profitability of a firm, which can affect a firm's capacity to invest in R&D. Employees is a control describing the number of employees included as a firm size proxy. Likewise, the total assets of a firm serve as a proxy for both the size and the resource availability. The efficiency of R&D spending is also controlled for through the control R&D per employee. This variable is computed by dividing the research and development expense by the number of employees. Sales is the control variable representing the total sales as a control for firm market size. The final internal firm characteristic control is capital expenditures, included to represent investments in physical capital which accounts for broader investment activity. The last and differently focused control factor is related to AI activity, namely Firm AI age. Firm AI age illustrates the number of years since a firm's first AI patent filing, representing experience with AI which could potentially influence response strategies due to prior AI involvement. All control variables are measured at the firm-year level and reflect established practices in empirical innovation research. Specifically, they align with control structures used in studies such as Coad et al. (2015), which account for firm size, capital investment, R&D efficiency, and firm age when analyzing innovation outcomes.

3.3 Empirical analysis

To empirically analyze the relationship between AI-driven disruption and incumbent R&D intensity, discover the effect of the moderators and thus test the hypotheses outlined in Chapter 2, this study employs the fixed-effects regression model. This type of regression model accounts for unobserved firm-level factors that remain constant over time, which is suitable for the panel dataset of incumbent firms from 2015 to 2023. This approach focuses on within-firm variation to capture the estimated effects of industry-level AI-driven disruption on firm behavior over time. Five models are tested, starting with the main independent variable and controls that are tested in Model 1. Models 2 through 4 test each moderator separately through interaction terms, while Model 5 includes all variables, moderators and interactions simultaneously. In this way, both the direct and conditional effects of AI-driven disruption on R&D investment behavior are comprehensively tested. Standard errors are clustered at the firm level to address potential correlation and heteroskedasticity. The regression equation below incorporates the variables from Section 3.2, including interaction terms as well as firm (i) and time (t) fixed effects, as follows:

$$
\begin{aligned}
RD\_intensity_{(it)} &= \beta_0 + \beta_1 \cdot Disruptor\_AI_{(it)} + \beta_2 \cdot Dynamism_{(it)} + \beta_3 \\
&\cdot Munificence_{(it)} + \beta_4 \cdot Complexity_{(it)} + \beta_5 \\
&\cdot (Disruptor\_AI \times Dynamism)_{(it)} + \beta_6 \\
&\cdot (Disruptor\_AI \times Munificence)_{(it)} + \beta_7 \\
&\cdot (Disruptor\_AI \times Complexity)_{(it)} + X'_{(it)} \cdot \gamma + \mu_i + \varepsilon_{it}
\end{aligned}
$$

Where:

$RD\_intensity_{it}$ = ratio of R&D expenditures divided by sales for firm i and time t

$Disruptor\_AI_{it}$ = log of average AI patents filed by disruptors in the same industry-year

$Dynamism_{it}$ = 5-year standard deviation of industry sales

$Munificence_{it}$ = 5-year industry sales trend (slope coefficient)

$Complexity_{it}$ = industry Herfindahl index (sales concentration)

Interaction terms = product of Disruptor_AI and each moderator

X'_{it} = vector of control variables as described in Section 3.2.4

μ_i = firm fixed effects

ε_{it} = error term

Chapter 4 – Findings

This chapter will present the empirical results of the statistical analysis. It includes a summary of the key descriptive statistics and the correlations between the variables, followed by a discussion of the fixed-effects regression models that investigate the relationship between AI-driven disruption and R&D intensity.

4.1 Descriptive statistics

In Table 1 an overview can be found of the mean, standard deviation (SD), and Pearson correlation coefficients of the variables used in the statistical analysis based on a sample size of 2,255 observations. These descriptive statistics and correlations are reported based on the raw dataset to accurately reflect the distribution of the sample. The mean and standard deviation columns show that the dependent variable, R&D intensity, has a mean of 0.108 and a standard deviation of 0.286. The dependent variable is expressed as a ratio, describing the R&D spending as a fraction of sales. These values are in line with expectations, as they confirm that most firms invest relatively little in R&D compared to their size. In this case, firms on average dedicate approximately 10% of their sales to invest in R&D. Prior research notes that R&D intensity varies significantly across industries, with lower levels typically observed in sectors not classified as high-tech. In these industries, innovation can occur through activities that are not formally recorded as R&D expenditures, resulting in a relatively modest R&D investment as a share of total corporate spending (Cohen & Levin, 1989; Hall & Lerner, 2010). Notably, the maximum value of R&D intensity in the dataset is 12.705, which lies outside of the expected range between 0 and 1, suggesting the presence of an outlier or a possible data anomaly.

The independent variable, Disruptor AI, has a mean value of 1.171 and a standard deviation of 0.417, implying that a large portion of firms in the sample are exposed to disruptive AI technologies. However, the variation in the values of the IV may reflect differences in AI patenting exposure across industries. Since this variable is based on the natural logarithm of the average number of AI-related patents filed within each industry-year, its distribution likely captures both technological heterogeneity across sectors and temporal growth trends in AI patenting activity (Cockburn et al., 2018). The observed variance reflects the widespread adoption of AI and supports the proposition that disruptive technologies may influence firm-level innovation outcomes. Other remarkable values include the extremely high mean values for Dynamism (3,011,182) and Munificence (1,354,642), indicating that these environmental factors vary widely across industries and markets. The high values stem from the use of raw annual sales data in defining industry conditions, which naturally vary across different sectors like retail, pharmaceuticals, and manufacturing. In a similar vein, the financial variables display both high means and standard deviations, potentially reflecting firm size heterogeneity or presence of outliers. Especially Capital Expenditures has a noticeable standard deviation (3,969.78), likely as a result of skewed data or extreme values from for example multinational companies. The large standard deviations might raise potential concerns about the underlying data distribution. To address this and to enhance the robustness of the analysis, data normalization was applied through winsorization as mentioned in Section 3.1.2.

TABLE 1 DESCRIPTIVE STATISTICS

Variables	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) R&D Intensity	0.108	0.286	1.000														
(2) Disruptor AI	1.171	0.417	0.046	1.000													
(3) Dynamism	301182.18	239682.4	0.017	0.137	1.000												
(4) Munificence	135426.93	151370.37	0.004	0.302	0.813	1.000											
(5) Herfindahl	0.197	0.178	-0.069	-0.153	-0.259	-0.213	1.000										
(6) DisruptorAIxDynamism	370853.15	329682.01	0.031	0.514	0.888	0.828	-0.248	1.000									
(7) DisruptorAIxMunificence	179804.53	209420.23	0.026	0.563	0.747	0.926	-0.216	0.919	1.000								
(8) DisruptorAIxComplexity	0.216	0.204	-0.050	0.197	-0.170	-0.087	0.882	-0.065	-0.023	1.000							
(9) R&D per employee	50.516	86.141	0.305	0.006	0.062	0.029	-0.125	0.047	0.029	-0.109	1.000						
(10) Firm AI Age	12.545	10.203	-0.030	-0.044	0.049	0.048	0.031	0.017	0.019	0.020	-0.033	1.000					
(11) Assets	26729.358	58802.116	-0.058	-0.132	0.129	-0.042	-0.120	0.034	-0.075	-0.141	-0.011	0.144	1.000				
(12) Employees	36.208	72.789	-0.083	-0.110	0.110	-0.026	-0.042	0.032	-0.056	-0.056	-0.125	0.135	0.709	1.000			
(13) Net Income	1954.261	5942.119	-0.023	-0.055	0.121	0.047	-0.079	0.071	0.023	-0.083	0.098	0.092	0.701	0.361	1.000		
(14) Sales	17254.019	42476.649	-0.067	-0.121	0.148	-0.002	-0.047	0.068	-0.039	-0.097	-0.030	0.094	0.892	0.725	0.683	1.000	
(15) Capital Expenditures	1232.996	3969.778	-0.053	-0.096	0.148	0.015	-0.112	0.073	-0.015	-0.128	-0.021	0.104	0.837	0.661	0.548	0.788	1.000

The Pearson correlation matrix shows several strong correlations, offering insights into potential multicollinearity. As expected, the three moderating variables are highly correlated with their respective interaction terms, with all coefficients exceeding r = 0.88. This outcome is mathematically consistent with the construction of interaction terms as multiplicative functions, and it supports the use of mean-centering and specification of separate regression models for each moderator to avoid multicollinearity (Aiken & West, 1991). Additionally, Munificence and Dynamism are strongly correlated to each other with a correlation value of 0.813, which justifies the separation of their interaction effects into distinct models. The firm-level controls also show high intercorrelations, as their correlations all rise above 0.7 and especially assets and sales are strongly correlated (r = 0.892). In contrast, Firm AI Age shows low correlations with financial or performance-related metrics, suggesting that the time since AI adoption might not be linearly related to size or financial outcomes in this sample.

Remarkably, the dependent variable is only weakly correlated with most of the variables. Its highest correlational value with R&D per Employee is a moderate value of 0.305, which may not have been expected and could suggest a difference in conceptual definitions or data measurement inconsistencies. These findings suggest that firm-level characteristics are thus loosely related to R&D intensity. This implies that firm-level innovation behavior is multifaceted and likely subject to a more complex interplay of factors than what is captured in this simple pairwise correlations overview.

To assess multicollinearity among the independent and control variables, a Variance Inflation Factor (VIF) analysis was conducted using a pooled OLS regression. The results, presented in Table 3 (Appendix B), show that none of the variables exceed the commonly used VIF threshold of 10, with the exception of assets (VIF = 10.20). The VIF for Sales is also moderately elevated (6.65). These higher values are likely due to their shared role as proxies for firm size, as is common in empirical innovation studies that use multiple size indicators to control for scale effects (Cohen & Levin, 1989). Accordingly, multicollinearity is not assessed to be a major concern.

TABLE 2 FIXED EFFECTS REGRESSION

	Model 1	Model 2	Model 3	Model 4	Model 5
Disruptor AI	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D per employee	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Age AI	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Assets	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employees	0.000^{*}	0.000^{*}	0.000^{*}	0.000^{*}	0.000^{*}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net Income	-0.000^{**}	-0.000^{**}	-0.000^{**}	-0.000^{**}	-0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales	-0.000^{*}	-0.000^{*}	-0.000^{*}	-0.000^{*}	-0.000^{*}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Expenditures	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dynamism		-0.000			-0.000
		(0.000)			(0.000)
DisruptorAI x Dynamism		0.000			0.000
		(0.000)			(0.000)
Munificence			-0.000		0.000
			(0.000)		(0.000)
DisruptorAI x Munificence			-0.000		-0.000
			(0.000)		(0.000)
Complexity				-0.004	-0.005
				(0.004)	(0.004)
DisruptorAI x Complexity				-0.003	-0.002
				(0.004)	(0.004)
Constant	0.070^{***}	0.069^{***}	0.070^{***}	0.070^{***}	0.069^{***}
	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
Observations	2255	2255	2255	2255	2255
R^2	0.232	0.232	0.232	0.232	0.234
Prob > F	0.000	0.000	0.001	0.000	0.000

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2 Fixed effects regression

The results of the fixed-effects regression examining the relationship between AI-driven disruption and R&D intensity as a strategic response, along with the moderating effects of the three dimensions of industry uncertainty, are presented in Table 2. The analysis consists of five models that include different combinations of variables to test the hypotheses outlined in Chapter 2. All models use R&D intensity as the dependent variable. Model 1 tests the direct effect of the independent variable. Models 2 through 4 examine the effect of each moderator individually (Dynamism, Munificence, and Complexity), including the corresponding interaction terms. Testing the moderators individually in separate models allows for an assessment of the unique effect of each moderator on the relationship between AI-driven disruption and R&D intensity. Finally, Model 5 combines all components, the main effect of AI-driven disruption, the three moderators of industry uncertainty, and their interactions terms, offering a comprehensive evaluation of the direct as well as the moderating effects of the framework. A primary significance threshold of $p < 0.05$ is employed throughout the analysis. However, effects with $p < 0.1$ and $p < 0.01$ are also reported and noted as marginally significant and highly significant, respectively, to provide additional nuance.

4.2.1 *H1: AI-patenting activity by disruptor firms in an industry positively influences the R&D intensity of incumbent firms.*

The first hypothesis is not supported by the results. The coefficient of Disruptor AI is $\beta = 0.001$ across all of the five models with a standard error of 0.001. However, in neither of the five models does the independent variable show to be statistically significant ($p > 0.05$). Therefore, it can be concluded that there is no evidence that AI-driven disruption, measured by AI patent activity, has a significant direct effect neither positive nor negative on incumbents' R&D intensity.

4.2.2 *H2: Industry dynamism positively moderates the relationship between disruptor AI patenting activity and incumbent R&D intensity.*

The moderating role of dynamism on the relationship between AI-driven disruption and R&D response is tested in Model 2 through the interaction term DisruptorAIxDynamism. The interaction term shows extremely small coefficients of $ß = 0.000$ (SE = 0.000, $p > 0.05$) in both Models 2 and 5 and is thus not significant. This means that varying levels of dynamism within an industry do not significantly alter how incumbents respond to AI-driven disruption in terms of R&D intensity. The relationship is not strengthened nor weakened, and it can therefore be concluded that the second hypothesis is not supported.

4.2.3 *H3: Industry munificence positively moderates the relationship between disruptor AI patenting activity and incumbent R&D intensity.*

The third moderating hypothesis is tested in Model 3, including the interaction term DisruptorAIxMunificence to test whether munificence positively moderates the relationship between AI-driven disruption and R&D intensity. The interaction term of munificence remains statistically insignificant in Models 3 and 5, with negative coefficients close to zero ($ß = -0.000$, SE = 0.000, $p > 0.05$), contradictive to the hypothesized direction. Resource richness does not seem to significantly enhance how incumbents react to disruptive AI activity. We can thus conclude that the third hypothesis is not supported by the results.

4.2.4 *H4: Industry complexity (as measured by the Herfindahl index) negatively moderates the relationship between disruptor AI patenting activity and incumbent R&D intensity.*

Model 4 tests the moderating role of complexity on the relationship between AI-driven disruption and R&D intensity through the interaction term DisruptorAIxComplexity. In both Models 4 and 5, the interaction term for the moderating effect of complexity, measured via the Herfindahl index, shows negative coefficients of $ß = -0.003$ and $ß = -0.002$. The negative coefficients are consistent with the hypothesis and theory that in more complex industries, firms face greater challenges in interpreting and responding to AI-driven innovation. Their likelihood of increasing R&D investments in response to disruptor activity is thereby reduced. However, the estimates are not statistically significant given the standard error of 0.004 in both cases ($p > 0.05$). Therefore, there is no evidence that complexity modifies the relationship between AI-driven disruption and R&D intensity. This final moderating hypothesis is therefore not supported.

4.2.5 *Full model*

Model 5 presents the full model and includes the independent variable AI-driven disruption (DisruptorAI), the three moderators (Dynamism, Munificence, Complexity) and their interaction terms (DisruptorAIxDynamism, DisruptorAIxMunificence, DisruptorAIxComplexity) along with the control variables. Despite the inclusion of all components, the results show that none of the key theoretical predictors are statistically significant. The coefficient for AI-driven disruption remains positive ($\beta = 0.001$) but insignificant (SE = 0.001, $p > 0.05$). All three interaction terms that capture the moderators of industry Dynamism ($\beta = 0.000$, SE = 0.000), Munificence ($\beta = -0.000$, SE = 0.000), and Complexity ($\beta = -0.002$ and -0.003, SE = 0.004) are also insignificant ($p > 0.05$). Remarkably, the highest R-squared among the five models is reached in Model 5 ($R^2 = 0.234$). This value indicates that the model explains slightly more variation in R&D intensity compared to the other models. However, the increase is marginal and insufficient to support any of the hypothesized effects. Several firm-level control variables seem to be statistically significant predictors throughout the five models. Sales ($\beta = -0.000$, SE = 0.000) and Employees ($\beta = 0.000$, SE = 0.000) are marginally significant ($p < 0.01$), Net Income ($\beta = -0.000$, SE = 0.000) is significant at the 5% level ($p < 0.05$), and R&D per employee ($\beta = 0.001$, SE = 0.000, $p < 0.01$) is highly significant. These variables consistently show these significant associations with R&D intensity in all five models, indicating that internal firm-level factors are more influential determinants of R&D strategies than external industry-level disruption form AI technologies. Thus, while Model 5 provides a robust specification, its results do not support the hypothesized relationships between AI-driven disruption, incumbent R&D investment behavior, and industry uncertainty.

4.3 Robustness checks

To assess the reliability and credibility of the findings from the fixed effects regressions, a variety of robustness checks were conducted. These checks were designed to test whether the results found in the models, specifically the insignificant relationship between AI-driven disruption and incumbent R&D intensity, might be sensitive to alternative specifications, temporal dynamics, industry compositions, or measurement approaches. Each of the three robustness checks was applied consistently across the five regression models, to enable a symmetrical comparison with the main analysis.

4.3.1 Lagged AI Disruption

An initial concern is that firms may take time to recognize and adapt to AI-driven disruptions, as identifying opportunities regarding AI integration within business operations and processes often requires a substantial amount of research and time (Lee et al., 2022). Strategic decisions concerning R&D often involve planning cycles of multiple years, particularly within large incumbent firms. In order to test for the potential delay of R&D investments, the main predictor, Disruptor AI, was lagged by one year in each regression model. Additionally, interaction terms were created between this newly lagged variable and the industry moderators to evaluate the moderating effects of Dynamism, Munificence and Complexity considering the potential delay. As shown in Table 4 (Appendix C), the results of the lagged specification were mostly consistent with the results from the main analysis. Across these models, the coefficient for lagged Disruptor AI remained small and statistically insignificant (*ß* = -0.001 to -0.002, SE = 0.001, $p > 0.05$), indicating no evidence of a delayed AI-driven influence on R&D intensity. Notably, two of the interaction terms with the lagged moderator variables were weakly significant at the 10% and 5% thresholds. Lagged DisruptorAI x Dynamism showed a coefficient of *ß* = -0.000 in model 2 (SE = 0.000, $p < 0.1$) and Lagged DisruptorAI x Munificence had a coefficient of *ß* = -0.000 in model 3 (SE = 0.000, $p < 0.05$). However, the effects were subtle, negative, and contrary to the theoretical expectations in which positive moderation was hypothesized. Accordingly, while this robustness check accounts for the possibility of delayed R&D investments, the results do not provide evidence that firms adjust their R&D behavior in response to past disruptive AI activity in the industry. These findings suggest that either the effect is not present within a one-year time lag or that incumbent firms are not responsive to external technological disruption in their R&D investment decision in a robust way.

4.3.2 Industry Exclusion

The main regression included numerous different industries. Industries can differ in terms of their exposure to AI, the pace of innovation, and typical R&D behavior (Cockburn et al., 2018). A second concern might therefore be that the results from the main regression are affected by a few industries with extreme characteristics. To assess this possible effect, the models were re-run after excluding two key sectors, one at a time:

A) Excluding Pharmaceuticals (Industry Code 28)

Pharmaceutical firms can be characterized to be R&D-intensive, potentially behaving differently from other sectors in how they respond to AI-driven disruptive innovation. After excluding the observations from this industry, the five models were re-estimated. The results shown in Table 5 (Appendix D) remained consistent with the main analysis, in which AI-driven disruption was statistically insignificant across all models (*ß* = 0.000 and 0.001, SE = 0.001, p

> 0.05), and the interaction terms did not reach any significance either. Employees remained marginally significant ($\beta = 0.000$, SE = 0.000, $p < 0.1$), while Sales ($\beta = -0.000$, SE = 0.000, $p < 0.05$) and Assets ($\beta = 0.000$, SE = 0.000, $p < 0.05$) both reached a moderate significance at the 5% threshold. Net Income ($\beta = -0.000$, SE = 0.000, $p < 0.01$) and R&D per employee ($\beta = 0.001$, SE = 0.000, $p < 0.01$) were both highly significant. The other control variables remained stable and insignificant. The R-squared values were comparable among the five models ($R^2 = 0.168$ to 0.171). Therefore, it can be concluded that pharmaceutical firms do not affect the core findings.

B) Excluding Technology Services (Industry Code 73)

The second type of industry excluded was tech-oriented business service firms, with the particular focus in software and computing. These types of firms are important for the AI innovation ecosystem, and they might thus heavily skew the industry-level disruption effects. However, after excluding the firms in this industry, the results from the re-estimated models were consistent with the main analysis (Table 6, Appendix E). The AI-driven disruption coefficients remained statistically insignificant ($\beta = 0.000$ to 0.001, SE = 0.001, $p > 0.05$), and none of the interaction effects reached significance either. However, the moderator Dynamism did reach moderate significance in Model 5 ($\beta = -0.000$, SE = 0.000, $p < 0.05$). The control variables Net Income ($\beta = -0.000$, SE = 0.000, $p < 0.05$) and R&D per employee ($\beta = 0.001$, SE = 0.000, $p < 0.01$) showed the same significance levels as in the main regression, whereas the other variables were statistically insignificant. The R-squared values increased slightly ($R^2 = 0.294$ to 0.297), even though this did not translate into meaningful differences in interpretation. Accordingly, it can be concluded that the exclusion of tech firms does not change the findings and conclusion of the main analysis.

4.3.3 Alternative DV

The third and final robustness check that was performed, uses an alternative dependent variable (Table 7, Appendix F). The variable R&D intensity from the main analysis was swapped with a new dependent variable, namely the R&D-to-sales ratio. This metric is an alternative way to measure R&D effort, computed as the total R&D expenditures divided by firm revenue (Sales). In this way a scale-adjusted view of R&D behavior is obtained to ensure robustness with respect to variable construction. Across all five models using the R&D-to-sales ratio as the DV, the coefficient on AI-driven disruption remained positive but statistically insignificant ($\beta = 0.001$), with a consistent standard error of 0.001 ($p > 0.05$). In line with the main specification, the interaction terms for Dynamism, Munificence, and Complexity continued to be insignificant and the R-squared values remained modest (Model 5: $R^2 = 0.215$). Net Income ($\beta = -0.000$, SE = 0.000, $p < 0.05$) and R&D per employee ($\beta = 0.001$, SE = 0.000, $p < 0.01$) showed the same significance levels as in the main regression and the robustness check excluding the technology services industry, which reinforces their explanatory power. Sales reached a marginal significance level again ($\beta = -0.000$, SE = 0.000, $p < 0.1$), and the other control variables remained statistically insignificant. The overall model structure remained comparable to that of the main regressions. The findings of this final robustness check therefore support the conclusion that AI-driven disruption does not have a meaningful effect on R&D behavior of incumbent firms, regardless of the measure of that behavior.

Chapter 5 – Discussion & Conclusion

This final chapter will develop the overall conclusions from the executed study, derived after linking the theory to the empirical results. The first part will discuss what theoretical and empirical findings have been discovered, followed by limitations and possible future directions of the research. Managerial implications will be given, after which the study will be concluded in the final conclusion section.

5.1 Discussion

The aim of this thesis was to explore whether AI-driven disruptive innovation, proxied by the number of AI-related patent filings by disruptor firms, influences incumbent firms to strategically respond by increasing their R&D intensity. Drawing on the original concept of Christensen (1997) and established disruption theory, a theoretical framework was established in order to formulate a concise definition of the phenomenon of disruptive innovation. Strategic responses were also identified to distinguish different strategies and their potential outcomes, with a specific focus on R&D investment behavior. Additionally, it was examined whether the relationship between AI-driven disruptive innovation and R&D intensity is moderated by industry uncertainty, captured by the dimensions of dynamism, munificence, and complexity. While grounded in the established disruption theory and the recent work on AI as a general-purpose technology (Cockburn et al., 2018), the empirical findings contradict the theoretical expectations.

In contrast to the formulated hypotheses, the findings from the fixed-effects regression models indicated that there is no statistically significant direct relationship between AI-driven disruptive innovations and the R&D intensity of incumbent firms. This suggests that even in industries where AI-driven innovation is intensifying, incumbents do not necessarily respond by scaling up on their R&D investments. This finding is consistent across all models and robustness checks, including a lagged predictor, industry exclusions and an alternative dependent variable. A possible explanation could be that AI-driven disruption may not yet be perceived as urgent or threatening enough to affect internal innovation responses, particularly if the disruptions are in the early stages of diffusion or occur outside of an incumbent's core market. Moreover, AI patent activity may not serve as a strong signal for managers, especially in complex environments, where firms face multiple potentially overlapping signals and might struggle to distinguish the disruptive threats (Cockburn et al., 2018). This aligns with the low observed correlation between AI-driven disruption and R&D intensity.

Another key realization is that R&D intensity may not reflect the full range of incumbent response strategies. As discussed in Chapter 2, incumbents have various other strategic response strategies besides internal innovation. For example, the theory on organizational ambidexterity (Schindler et al., 2024) and adaptive strategic responses (Charitou & Markides, 2003) suggest that firms may rather react by changing their organizational structure. Therefore, the non-significance of R&D intensity may imply that R&D is not the primary strategic means for dealing with disruptive AI adaptation.

Furthermore, industry conditions did not moderate the relationship between the independent and dependent variable. Even though the literature suggest that firms in dynamic or munificent environments are more likely to innovate (Dess & Beard, 1984), the findings from this study indicate otherwise. One explanation may be that firms in highly dynamic industries already operate at higher baseline levels of innovation, limiting the room for further increases in response to AI-driven disruption. Similarly, firms in resource-rich environments may spread their chances across various domains rather than focusing on R&D only, particularly if it is not clear whether AI activity will result in positive performance outcomes. Regarding industry complexity, the fact that there was no statistically significant moderating effect may indicate that firms struggle to respond to AI-driven innovation when operating in environments with conflicting signals or concentrated market structures.

Notably, internal firm-level factors such as R&D per employee, sales, and net income were significant predictors of R&D intensity. This reinforces the importance of firm-level absorptive capacity (Cohen & Levinthal, 1990), suggesting that an incumbent's ability to respond to disruption is influenced more by internal resources and competencies than by industry-level signals. Hence, strategic responses to AI-driven disruption do not seem to be consistent across industries but instead vary according to individual firm-specific capabilities and circumstances.

5.2 Limitations and future research directions

While this study contributed to the literature with meaningful insights into how incumbent firms respond to AI-driven disruption, several limitations have to be acknowledged that may open up avenues for future research.

A first limitation concerns the temporal scope of strategic responses. In the first robustness check, a one-year lag was tested to account for potential delays in firm reactions to AI-driven disruption. However, the results remained insignificant, suggesting that this time window may have been too short to capture strategic adaptation. Particularly in R&D intensive industries planning and execution cycles can cover multi-year periods. Future research could explore extended lag structures, rolling averages, or distributed lag models to better account for the time it might take incumbents to familiarize themselves with technological signals and convert these into innovation investments. Additionally, this could uncover whether certain responses only become visible after AI-driven innovation reaches a more mature phase in the S-curve of innovation.

Secondly, the use of AI-related patent filings as the proxy for disruptive innovation introduces measurement limitations. Although consistent with previous research, patent data may not fully reflect the market or commercial impact of AI technologies. Patents capture the presence of newly developed ideas but not necessarily their implementation or success in the industry. Moreover, not all firms patent their technologies, especially in software-intensive areas where alternative forms of intellectual property are used. Future studies could therefore combine patent data with complementary indicators, such as product launches, venture capital funding of AI startups or AI adoption rates derived from surveys or text analysis. This allows them to develop a more comprehensive disruption measurement index.

A third limitation concerns the scope of R&D intensity as a strategic response in this study. The analysis focused exclusively on R&D intensity as a measurable and widely accepted proxy for innovation investment. However, as discussed in the theoretical framework, incumbents can also pursue other forms of response strategies. This may include the acquisition of AI startups, the establishment of separate AI business units, or alliances with external partners. Such forms of adaptation may be more representative of a firm’s flexibility in responding to AI-driven disruption, especially when R&D systems are constrained or not easily redirected. Future studies could explore multiple measures of strategic responses, including for example merger and acquisition activity as well as organizational restructuring events, to provide a more holistic view.

Additionally, the study is geographically limited to include only North American firms. While this choice ensured consistency in data availability and regulatory context, it limits the generalizability of the findings. Innovation ecosystems, regulatory frameworks and data infrastructures may differ significantly across regions. Future cross-country or comparative studies could examine how institutional and cultural factors shape the response to AI-driven disruption in different contexts.

Lastly, a key limitation of this thesis is the constrained timeframe in which the research was conducted. The academic calendar and deadlines did not allow for a greater scope considering the variable selection, more extensive data analyses, or exploration of other model specifications. As a result, certain aspects of the topic had to be prioritized and selectively analyzed. While some of the limitations are likely a consequence of the constrained timeframe, they also open up new opportunities for future research directions.

5.3 Managerial and academic contributions

Although the results of the empirical analysis did not confirm the hypothesized relationships between AI-driven disruptive innovation and R&D intensity, the findings offer meaningful insights for managerial decision-making.

Firstly, managers should not assume a direct link between AI activity in the industry and the need for increased R&D investment. No significant relationship was found in this study, which indicates that external factors may not fully reflect disruptive threats that support internal innovation responses through R&D. Firms should instead evaluate whether specific features of AI-driven innovations are directly relevant to their competitive position, customer demands, and technological capabilities. Accordingly, firms can make well-informed decisions and avoid inefficient innovation investments that may not align with actual competitive needs.

Moreover, a second contribution for managers is the importance of strengthening internal innovation capabilities. The firm-level variables R&D per employee, Net Income, and Employees across the models were consistently significant predictors of R&D intensity in the regression. Organizations with good internal innovation infrastructures, a specialized workforce, and well-organized decision-making might be better prepared to engage in innovation investment regardless of external AI-driven disruptive pressures. Managers should therefore prioritize building internal innovation processes and talent internally, as this may be more beneficial for long-term adaptability than reactive R&D investment behavior.

Besides the managerial relevance, this study also contributes to the academic literature by refining the theoretical assumptions about how firms respond to AI-driven disruptive innovation. The study adds nuance to the established disruption theory and clarifies that AI-driven disruptive innovation does not automatically pressure incumbents to increase their R&D investment. No significant relationship was found between disruptive AI activity and R&D intensity, which suggests that disruption does not have a uniform influence on all firms in an industry. The impact of disruptive innovation is determined by a firm's unique strategic positioning, rather than by general industry signals.

Additionally, this study reinforces the role of organizational readiness and absorptive capacity (Cohen & Levinthal, 1989). It is emphasized that the ability to respond effectively depends less on external disruption pressures and more on internal structures, resources, and capabilities. The study demonstrates the central role of internal competence in shaping the adaptive innovation behavior of firms, integrating the understanding in the literature on disruptive innovation and organizational learning.

5.4 Conclusion

This thesis explored the relationship between AI-driven disruptive innovation and R&D intensity of incumbent firms, moderated by the three key dimensions of industry uncertainty. Drawing on disruption theory and empirical data from publicly listed North American firms in the period from 2015 to 2023, the results revealed no significant effects. The lack of support for the formulated hypotheses highlights the nuanced nature of firm responses to AI. Contrary to the theoretical expectations, external AI-driven disruptive pressure does not automatically translate into internal R&D innovation efforts. Instead, responses are influenced by internal firm capacities, managerial perceptions, and potentially strategic actions that are not based on R&D. The results highlight the need for a more contextualized and situationally grounded understanding of disruption in the age of AI. By combining robust empirical analysis with a strong theoretical foundation, this thesis contributes to the growing literature on innovation strategy under disruption. It underscores the importance of looking beyond traditional indicators and emphasizes that adaptation is less about reacting to disruption signals and more about being structurally and cognitively prepared for them.

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Appendices

Appendix A

Declaration on the Use of AI Tools

By submitting this thesis, I acknowledge that I have read and understood the requirements regarding the ethical and responsible use of AI tools as outlined by Tilburg University and I agree to adhere to them as stated in the syllabus.

In the process of writing this master thesis, I used ChatGPT to help me gather data and create my dataset in Stata. ChatGPT (OpenAI GPT-4) was utilized at various dates between April and June 2025. The AI tool provided me with commands that I could use in the program Stata in order to be able to create my variables and perform the regressions. Especially when something in my data was not correct, ChatGPT could quickly identify what I would have to change in order to fix the error or issue. After the main regression, I discussed with the AI tool several options on what robustness checks I could perform and again it helped me find the right commands.

Moreover, I have used ChatGPT to check and correct the grammar and style to ensure there are no mistakes in the text. In this way, I hoped to improve the flow and coherence of my text.

Lastly, I used the AI tool Elicit to find several sources for my literature review. By asking a research question or inserting a few key words, this tool assisted me in searching academic articles on a broad spectrum. This tool was especially helpful in the first period of the writing process, as I had to gather many articles for establishing the theoretical background.

Generally, AI tools have been useful in assisting me gather sources and guide me in the program Stata to perform the regression analysis. However, I am well-aware of the limitations of such tools and have at all times checked its output and only used it to complement my own work.

Appendix B

TABLE 3 VIF ANALYSIS

Variable	VIF	1/VIF
Assets	10.20	0.098070
Sales	6.65	0.150325
Capital Expenditures	3.54	0.282691
Net Income	2.98	0.335029
Employees	2.44	0.410645
R&D per employee	1.09	0.916207
Firm AI Age	1.05	0.954491
Disruptor AI	1.02	0.976126
Mean VIF	3.62	

Appendix C

TABLE 4 LAGGED AI DISRUPTION

	Model 1	Model 2	Model 3	Model 4	Model 5
Lagged Disruptor AI	-0.002	-0.002	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D per employee	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm AI Age	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Assets	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employees	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net Income	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Expenditures	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dynamism		-0.000			0.000
		(0.000)			(0.000)
Lagged Disruptor AI x Dynamism		-0.000*			0.000
		(0.000)			(0.000)
Munificence			-0.000		-0.000
			(0.000)		(0.000)
Lagged Disruptor AI x Munificence			-0.000**		-0.000
			(0.000)		(0.000)
Complexity				-0.005	-0.006
				(0.005)	(0.005)
Lagged Disruptor AI x Complexity				-0.004	-0.007
				(0.009)	(0.009)
Constant	0.069***	0.068***	0.068***	0.069***	0.068***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
Observations	1323	1323	1323	1323	1323
R^2	0.344	0.346	0.348	0.345	0.349
Prob > F	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix D

TABLE 5 INDUSTRY EXCLUSION: PHARMACEUTICALS

	Model 1	Model 2	Model 3	Model 4	Model 5
Disruptor AI	0.000	0.001	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D per employee	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm AI Age	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Assets	0.000**	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employees	0.000*	0.000*	0.000*	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net Income	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Expenditures	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dynamism		-0.000			0.000
		(0.000)			(0.000)
DisruptorAIx Dynamism		0.000			0.000
		(0.000)			(0.000)
Munificence			-0.000		-0.000
			(0.000)		(0.000)
DisruptorAIx Munificence			0.000		-0.000
			(0.000)		(0.000)
Complexity				-0.006	-0.007*
				(0.004)	(0.004)
DisruptorAIx Complexity				-0.002	-0.001
				(0.004)	(0.003)
Constant	0.075***	0.074***	0.074***	0.075***	0.074***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Observations	2041	2041	2041	2041	2041
R^2	0.168	0.169	0.169	0.168	0.171
Prob > F	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix E

TABLE 6 INDUSTRY EXCLUSION: TECHNOLOGY SERVICES

	Model 1	Model 2	Model 3	Model 4	Model 5
Disruptor AI	0.000	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D per employee	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm AI Age	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Assets	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employees	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net Income	-0.000^{**}	-0.000^{**}	-0.000^{**}	-0.000^{**}	-0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Expenditures	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dynamism		-0.000			-0.000^{**}
		(0.000)			(0.000)
DisruptorAI x Dynamism		-0.000			0.000
		(0.000)			(0.000)
Munificence			-0.000		0.000
			(0.000)		(0.000)
DisruptorAI x Munificence			-0.000		-0.000
			(0.000)		(0.000)
Complexity				-0.003	-0.004
				(0.004)	(0.004)
DisruptorAI x Complexity				-0.001	-0.002
				(0.005)	(0.004)
Constant	0.055^{***}	0.053^{***}	0.054^{***}	0.055^{***}	0.052^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	1780	1780	1780	1780	1780
R^2	0.294	0.295	0.294	0.294	0.297
Prob > F	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix F

TABLE 7 ALTERNATIVE DV

	Model 1	Model 2	Model 3	Model 4	Model 5
Disruptor AI	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D per employee	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm AI Age	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Assets	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employees	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net Income	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales	-0.000*	-0.000*	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Expenditures	0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dynamism		-0.000			-0.000
		(0.000)			(0.000)
DisruptorAI x Dynamism		0.000			0.000
		(0.000)			(0.000)
Munificence			0.000		0.000
			(0.000)		(0.000)
DisruptorAI x Munificence			-0.000		-0.000
			(0.000)		(0.000)
Complexity				-0.007	-0.007
				(0.004)	(0.004)
DisruptorAI x Complexity				-0.003	-0.001
				(0.004)	(0.004)
Constant	0.072***	0.071***	0.072***	0.072***	0.071***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	2255	2255	2255	2255	2255
R^2	0.212	0.213	0.213	0.213	0.215
Prob > F	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$