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Finding the Digital Shortcut

A study on digital acquisitions as a means of acquiring digital capabilities for non-digital businesses

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Sammanfattning

Examensarbetets titel: I jakt på en digital genväg - En studie om digitala uppköp i syfte att erhålla digitala färdigheter för icke-digitala företag.

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Författare: David Ruichen Zhou, Nils Engman

Handledare: Antonio Marañon

Fem nyckelord: Digital M&A, digitala patent, digital transformation, digitala förmågor, two-way fixed effects regression

Forskningsfråga: I vilken utsträckning leder uppköp av digitala företag till en förändring av ett, icke-digitalt, företags digitala förmågor?

Syfte: Målet med studien är att kunskapsmässigt bidra till företag och investerare som vill förbättra ett företags digital förmågor genom uppköp av mindre digital bolag.

Metod: Studien upprättades med en kvantitativ metod och deduktiv ansats med hjälp av data från sekundära källor. Två tids- och entitetsfasta regressionsmodeller implementerades. En med kort tidsram och en med lång tidsram.

Teoretiska perspektiv: Studiens teoretiska ram bygger på teorin om resurser och förmågor och i förlängningen, dynamiska förmågor och digitala förmågor. Forskning om digitala förvärv och digitala möjligheter är tunt och mestadels ett outforskat område. Tidigare forskning inom området av Hanelt et al. (2021) och Tang, Fang & Jiang (2022) användes som grund för studien.

Resultat: Digitala uppköp har en statistisk signifikant korrelation till digitala förmågor. Korrelationen är positiv på kort sikt och negativ på lång sikt.

Slutsats: Denna studie fann att digitala förvärv kanske inte är det mest effektiva sättet att öka digital kapacitet på lång sikt. Det rekommenderas därför att chefer noggrant utvärderar användningen av digitala förvärv som en metod för att erhålla önskad tekniska kapabiliteter.

Abstract

Title: Finding the Digital Shortcut - A study on digital acquisitions as a means of acquiring digital capabilities for non-digital businesses

Seminar date: 11 January 2022

Course: FEKH39, Degree Project Undergraduate level, Business and Data Analytics, Undergraduate level, 15 University Credits Points (UPC) or ECTS‐cr)

Authors: David Ruichen Zhou, Nils Engman

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Key words: Digital M&A, digital patents, digital transformation, digital capabilities, two-way fixed effects regression

Research question: To what extent do acquisitions of digital companies lead to a change in digital capabilities for non-digital businesses?

Purpose: The aim of the study is to further improve the empirical foundation for companies and investors interested in performing digital acquisitions with the goal of improving their digital capabilities.

Methodology: The study was done with a quantitative method and a deductive approach using data from secondary sources. Two time and entity fixed effects regression models were implemented. One with a short time frame and one with a long time frame.

Theoretical perspectives: The theoretical framework of the study is based on the theory about resources and capabilities and in extension, dynamic capabilities and digital capabilities. Research into digital acquisitions and digital capabilities is scarce and mostly an unexplored area. Previous research in the field by Hanelt et al. (2021) and Tang, Fang & Jiang (2022) was used as a foundation for the study.

Result: Digital acquisitions have a statistically significant correlation with digital capabilities. The correlation coefficient is found to be positive in the short term and negative in the long term.

Conclusions: This study found that digital acquisitions may not be the most effective way to increase digital capabilities in the long term. It is thereby recommended that managers carefully evaluate the use of digital acquisitions as a method of obtaining desired technological capabilities.

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David Zhou & Nils Engman

Glossary

Digital technologies:
Combinations of information, computing, communication, and connectivity technologies (Bharadwaj et al., 2013).

Digital acquisitions:
Acquisition of companies that intensely leverage digital technologies (Hanelt et al., 2021).

Digital patents:
Digital patents are patents that highly leverage digital technology (Hanelt et al., 2021).

Digital capabilities:
"A firm's skill, talent, and expertise to manage digital technologies for new product development" (Khin & Ho, 2018, p.182).

Electric utility:
An electric power company that takes part in the generation, distribution and sale of electricity (USC, 2011).

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1. Introduction

In this chapter, the background of the study is presented followed by the problematization, the purpose, the research question and lastly the boundaries of the study.

1.1. Background

Businesses exist in an environment rich with various data. Data points are constantly being generated from different activities and phenomena, whether it be surveys, financial transactions, heartbeats, movements from one location to the other, reactions to social media posts, and google searches. The accessibility to such a library of information poses additional challenges to businesses that have poor data management capabilities but for those who can handle such data, it can be immensely profitable as shown by Microsoft and Amazon (Moore & Tambini, 2018). The use of such data is dependent on digital technologies, which are defined by Bharadwan et al (2013, p.471) as “combinations of information, computing, communication, and connectivity technologies”. The first four companies (Amazon, Google, Apple and Microsoft) to reach a market cap above a trillion dollars were all in the tech industry and highly sufficient at leveraging such digital technologies (Chang, 2021) .

While many companies use digital technologies to some degree, the scope and diversity of their use are expanding (Gressel et al., 2020). Many firms are currently undergoing a digital transformation, which may be described as “a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies” (Vial, 2021). Digital technologies are no longer supportive technologies but something that is or could be, at the core of the company's strategy and vision. For example, car manufacturers saw the potential to improve customer satisfaction by improving the user interface through implementing better digital tools such as displays with a broader functionality than previously or by letting the user monitor his or her car through a mobile app (Winkelhake, 2018). Digital activities can be outsourced to other firms, but doing so can create harmful dependencies and security issues. To avoid these concerns, firms may choose to develop their capability instead.

Digital capabilities, defined as a “firm’s skill, talent, and expertise to manage digital technologies for new product development” (Khin & Ho, 2018, p.182), are improved when a company goes through a digital transformation. Improved digital capabilities have moreover been found to lead to better firm performance, with the effect being partially mediated by digital innovation (Khin & Ho, 2018; Hanelt et al., 2021; Tang, Fang & Jiang,2022).

1.2. Problem formulation

With the considerable potential for substantial value creation, it is no surprise that companies are seeking methods to acquire digital capabilities. This is evidenced by the increasing demand for data and engineering professions (IDC & Lisbon Council, 2022). According to the International Data Corporation (IDC) and the Lisbon Council think tank (2022), the gap between the supply and demand of data professionals in the European Union (EU) will be expected to grow. In 2025 there will be a need for 5.3 per cent more data professionals than what is supplied, and they predict this gap will grow to 7 per cent in 2030. According to Davenport & Patil (2022), the data scientist profession is projected to expect more growth than almost any other profession by 2029 in the United States.

With the hopes of rapidly improving their digital capabilities, some companies choose to buy or invest in smaller companies. According to Tang, Fang & Jiang (2022) the value of digital mergers and acquisitions (M&A) deals globally has more than doubled over the last five years, and digital deals now account for 24% of the entire M&A market (Tang, Fang & Jiang, 2022).

By purchasing or investing in a smaller company, the number of people with digital skills can improve rapidly. These people could, in turn, be used to improve the skills of the acquiring company and help it in its transformation journey. These acquired assets may be difficult to obtain in other ways in part due to the tough competition for talent for digital skills and experience in Europe and North America. Acquiring data might be another reason for purchase. Some companies have huge amounts of data that could be of strategic value to a larger company. For example, a digital company that has a lot of data about people's online shopping behaviour could be bought up either because the acquirer wants to improve its own products or services or because it wants to hinder other companies from using the acquired companies' services. The acquired company could also be a software company, and even without troves of data it could own products and services which could work well with the acquirer's digital strategy.

Companies that try to keep up with rapid digital innovation want to know how to improve their digital capabilities fast. One way of doing so is by digital acquisition, defined as the acquisition of companies that intensely leverage digital technologies (Hanelt et al., 2021). Digital acquisition is a new research field. Currently, there are only a few studies that have touched on the subject, each from a distinct angle and with different focuses. These are presented in Chapter 2. The studies show a positive correlation between digital M&As and digital innovation, in part mediated by digital capabilities. Studies have also shown that digital capabilities and digital innovation lead to improved firm performance. However, due to the limited number of studies, along with each of their delimitations, there is a need for further examination of the correlation between digital M&As and digital capabilities.

1.3. Research purpose

The effects of digital acquisitions on digital innovation could be a useful tool for understanding the potential impacts of these transactions on individual firms and for making informed decisions about the benefits and risks of participating in digital acquisition activity. By providing an analysis of the relationship between digital acquisitions and digital capabilities, this study aims to provide a foundation for companies and investors to understand the potential implications of whether digital capabilities affect digital acquisitions.

1.4. Research question

To keep the research focused and aligned with the purpose of the study, the following research question was formulated:

To what extent does the acquisition of digital companies lead to a change in digital capabilities for non-digital businesses?

1.5. Delimitations

There are several limitations that were considered in this study. Most importantly the study was focused on a single industry, the electric utilities industry. The electric utility industry is a highly complex industry that is rapidly changing due to climate change and new technologies (Brody, Rogers & Siccardo, 2019; McLelland, 2021). Electric utility companies can use digital tools to optimise wind turbines, better simulation of electricity consumption and production, improve service and more (Siemens, 2022; E.ON, 2022). Electric utilities are not an industry that has leveraged digital tools to a large extent historically but an industry that could benefit from it. These factors together made electric utilities an interesting industry to analyse. Since the study by Hanelt et al. (2021) focused on auto manufacturers, as a representation of the overall industrial industry, it remained to see whether the results would hold true in the electric utilities industry.

2. Theoretical framework and formulation of hypothesis

In this chapter, the underlying theory is presented, beginning with general M&A theory and then moving on to digital M&A. A presentation of underlying theories is then presented, moving from resource-based theory, to dynamic capabilities to digital capabilities followed by a presentation of previous studies within digital M&A and digital capabilities. Finally, the hypothesis is motivated and formulated.

2.1. M&A

While mergers and acquisitions have become a prominent approach for organisations to introduce and implement new processes into their business, it has also come with a growing need for effective acquisition strategies (Grant 2021). Grant (2021) expresses how acquisitions may offer the fastest route to corporate growth, easing the need of developing new organizational capabilities internally, but stresses the risks it may pose if approached incorrectly. To effectively distinguish and analyse the effects of an M&A it becomes increasingly important to first understand how different types of M&A lend themselves.

Performing a successful acquisition is difficult and many things can go wrong (Grant, 2021). To do it successfully it is necessary to identify and understand the objectives behind the acquisition, and to see how they relate to the business's ability to provide the necessary knowledge, skills, and resources to actualize these strategies (Grant, 2021).

Grant (2021) outlines two main motivations for why acquisitions occur in the process of creating value. Financially motivated acquisitions are one of them and it refers to the ability to harness value through market inefficiencies, tax reduction possibilities, and financial engineering. Strategically motivated acquisitions, on the other hand, can be divided into several different types: horizontal acquisitions, geographical extension acquisitions, vertical acquisitions, and diversifying acquisitions (Grant, 2021). The acquisition of digital firms does not fit into any of the aforementioned types as one principal motivation is to acquire resources and capabilities that are not easily transferable nor easily replicated, thereby requiring the acquisition of external resources.

Research has shown that the different classifications of M&A, as well as industry, have an impact and result in different types of M&A success. For instance, in a study by Rozen-Bakher (2017), they found that horizontal M&A led to improved integration success and synergy success in the industry sector, but not in the services sector. Other research, however, has been found to yield contradicting results, failing to find robust empirical support for such claims (Grant 2021). Thus, it becomes exceedingly important for a business entity to be able to identify and understand the objectives behind acquisitions, and to see how they relate to the business's ability to provide the necessary knowledge, skills, and resources to actualize these strategies (Grant, 2021). When it comes to digital acquisitions, it has become a trend for businesses to blindly incorporate data as described by Gressel et al. (2020). Managers may feel pressured into incorporating data and analytics as a consequence of the adversity and influences they face on both industrial and organizational levels (Gressel et al., 2020). Therefore it can be deemed important to first evaluate the business needs and objectives in whether or not an acquisition is appropriate (Gressel et al., 2020).

2.2. Digital M&A

Digital M&As are different from traditional M&As. Intangible assets play a much larger role, where the knowledge of the personnel, the reputation of the company, vital databases and more are all important factors that must be counted in to justify the decision of digital M&A (Tang, Fang & Jiang, 2022).

Many industries are undergoing digital transformations (Ebert & Duarte, 2018). New business models such as car-sharing platforms and telematic services are being increasingly common while climate change has led to a huge boost for electric vehicles (LLopis-Albert, Rubio & Valero, 2021). These changes will stir up car automotive manufacturers to undergo digital transformations (LLopis-Albert, Rubio & Valero, 2021). Traditionally non-digital industries, such as the automobile industry, have been shown to use digital M&As, as a way to avoid the time-consuming effort of improving their digital capabilities on their own. By engaging in digital M&A, companies do not have to risk competitors blocking access to digital knowledge (Gao & Iyer, 2006). Digital M&As have also been shown to function as a quicker, and more acute way of increasing the number of digital professionals in an organization, in comparison to participating in the digital talent recruitment frenzy (Tang, Fang & Jiang, 2022). They also gain by avoiding leaving the digital work to others, since outsourcing can lead to dangerous dependencies (Westerman et al., 2012).

So far, very little research has been done on digital innovation and digital M&A by non-digital acquirers. Hanelt et al. (2021) and Tang, Fang & Jiang (2022) both found that digital M&A's led to an increase in digital innovation. Hanelt et al. (2021) analysed the automotive industry while Tang, Fang & Jiang (2022) analysed a broad spectrum of industries in China, excluding only financial and digital firms as acquirers.

2.3. Digital capabilities

Markets regularly disappear, emerge and transform. For a company to succeed it must adapt to the ever-changing environment. In 1984, Wernerfelt introduced the resource-based view which shifted focus from the companies' products to the companies' resources such as technology and customer loyalty. In other words, Wernerfelt argued that the firm's resources determined how well it could adapt to change. This view got much appreciation and was further rooted by the discovery of Rumelt (1991) that intra-industry differences in profit between firms were greater than inter-industry differences. Where intra-industry differences are greater, the firm's resources are strategically more important than the choice of industry.

Teece et al (1997) identified a key issue with the resource-based view, namely the connection between the firm resources and the business environment. Teece et al argued that firms' resources do not necessarily and inherently have the ability to provide a competitive advantage and that the resources have to fit the environment. To remedy this gap they presented the term dynamic capabilities for “firms that can deliver timely responsiveness and rapid and flexible product innovation, coupled with the management capability to effectively coordinate and redeploy internal and external competencies” (Teece et al., 1997, p.515). In other words, firms with dynamic capabilities can close the gap between the firm's resources and the fit to the environment through timely action, product innovation and good managers that can utilize the capabilities of the firm. The only diversification justifiable is “diversification that builds upon or extends existing capabilities” (Teece et al., 1997, p.529), such diversification is justifiable only if the firms’ traditional industry is declining (Teece et al., 1997). According to Khin & Ho (2018), digital capability can be seen as a form of dynamic capability. The implication is that an organization can use digital capability to innovate and manage internal and external competencies. Khin & Ho (2018, p.182) describes digital capabilities as “a firm’s skill, talent, and expertise to manage digital technologies for new product development”. Improving the digital capabilities of a firm thus implies that the firm is more skilled at leveraging digital technologies for product development.

A company can improve their digital capabilities in two main ways, either internally or externally (Hanelt et al., 2021). To do so internally, companies can make use of reorganization, but the results of which cannot necessarily be said to be predictable as well as them becoming potentially time-consuming processes (Hanelt et al., 2021). Therefore it may not be appropriate in a turbulent market (Hanelt et al., 2021). In an external process, on the other hand, an organization can choose to hire digital professionals instead, building strategic alliances/joint ventures or pursue digital M&A (Hanelt et al., 2021).

2.4. Previous Studies

Based on our literature review, we have observed that most studies focus on firm performance and its relationship with digital M&A in general terms. However, we find studies reflecting the concern of digital capabilities in relation to a firm's acquisitions to be scarce. Hanelt et al. (2021) investigated the correlation between digital acquisitions and digital capabilities in their paper *Digital M&A, digital innovation, and firm performance: an empirical investigation*. In their study, they limited their scope by solely looking at the top 30 OEM auto manufacturers. They found a positive correlation between digital M&A and a digital knowledge base (equivalent to digital capabilities). The digital knowledge base acts as a partial mediator between digital M&As and digital innovation. In other words, digital M&As affect digital acquisitions both directly and through the improvement of a digital knowledge base. Hanelt et al. (2021) also investigated the effect of digital innovation on firm performance, which was found to be positive.

Tang, Fang & Jiang (2022) studied the effect of digital M&As on market value in China. They identified 42 digital industries and then marked each M&A that had a target company within one of the digital industries as a digital M&A. Only company acquisitions within the financial sector were removed. Tang, Fang & Jiang (2022) found that digital M&As have a positive value effect on market value. They also found that this effect was achieved partially through increased digital innovation, which they defined as the number of patents granted or applied for. In this paper, patents are seen as a measure of digital capabilities rather than digital innovation and thus Tang, Fang & Jiang's results show that the positive effect on market value by digital M&As is mediated by digital capabilities as defined in this paper.

Khin & Ho (2018) did a survey study on 105 small to medium-sized companies in Malaysia. They looked at digital capabilities, digital innovation and firm performance but not at M&As. The results are similar to the ones presented by Hanelt et al. (2021) and Tang, Fang & Jiang (2022), showing a positive correlation between digital capabilities and digital innovation as well as between digital capabilities and firm performance. Considering the limited scope of the previous studies it could be of interest to further investigate the effect of digital M&As on digital capabilities.

2.5. Formulation of hypothesis

Studies in the existing literature have examined the impacts of the type of acquisition in relation to its success, showing that by exploring the types of acquisition by using the traditional classifications, a deeper understanding in regard to the influence of the types of acquisition can be identified. The existing literature, however, has been unable to provide consistent evidence of robust empirical outcomes from M&As, since results have been shown to differ greatly between industries and acquisition types (Grant, 2021). It is suggested that the discrepancies in the results pertain to the sizable difference in circumstances, such as the current capabilities, and goals between the companies involved (Rozen-Bakher, 2017). Thus, we find a reason to investigate whether these results are applicable to digital acquisitions, considering that it may prove to yield different results given that it has a more explicitly defined goal. Moreover, we find a need to investigate whether digital acquisitions can be used to accelerate the process of acquiring digital capabilities.

With the growing demand for digital capability, it is possible to indicate that the existing literature lacks studies that examine the influence of specifically digital acquisition as a means of deriving digital capability for traditionally non-digital acquirers. To the best of our knowledge, only two studies have been made on the subject, with one study focused on the industrial automobile industry (Hanelt et al., 2021) while the other, on a broader spectrum of industries in China, excluding only financial firms and digital firms as acquirers (Tang, Fang et Jiang, 2022).

Lastly, the digital acquisition literature lacks research in relation to the effects of the acquisition on digital capabilities over time. Thus, we find a need to address whether there is evidence to suggest that digital acquisitions may have different implications on digital capability in the short- and long term. Consequently, provided what has been stated, this paper will examine the following research question:

To what extent do acquisitions of digital companies lead to a change in digital capabilities for non-digital businesses?

Following the research question, we propose a hypothesis:

Hypothesis 1*: There is a relationship between the acquisition of digital companies and digital patents for non-digital businesses.*

In previous studies, digital patents have been implemented as a proxy for a firm's digital capabilities. Thus, a similar approach was chosen here.

3. Methodology

This section aims to describe the authors' choice of method and the structure of the study's design and implementation. First, an explanation is given for the choice of research approach and research design along with delimitations for the study. The authors then provide an explanation of the method used in the collection of empirical data, as well as the selection process for the sample of firms used in the analysis. The section ends with a discussion of the methodology in relation to credibility and validity.

3.1. Research approach

The objective of this study was to investigate whether *Digital Acquisitions* impact a firm's *Digital capabilities*. To this end, a quantitative, deductive research approach using secondary data was adopted given the purpose and aim of the study. A quantitative research method refers to the collection and analysis of data that is based on numerical measurements and parametric statistical analysis (Bryman & Bell, 2017). In a quantitative research study, data is collected on a specific topic using standardized instruments and statistical methods, such as surveys or experiments. The data is then analysed using statistical techniques suitable for quantitative data, such as regression analysis, to identify inherent patterns and relationships in the data (Bryman & Bell, 2017).

Quantitative research has been chosen for this study as it allows for the analysis of large amounts of data and enables for identification of trends and relationships that may not be apparent in qualitative or smaller studies (Bryman & Bell, 2017). This helped to provide a more objective and unbiased view of the topic being studied and can help in deriving more generalizable conclusions. Furthermore, employing a deductive research approach allows for the testing of specific hypotheses or theories about the relationship between different variables. By collecting data on variables and analysing the data using statistical techniques it was then possible to determine whether the hypothesis was supported by empirical quantitative data, and furthermore, the model may be used to make more accurate predictions about future trends or patterns (Bryman & Bell, 2017).

3.2. Research design

In order to analyse the impact of the acquisition on the company's digital capabilities, we implemented an event study methodology. An event study is a statistical method that is used to evaluate the impact of a specific event on an outcome of interest (Halpern 1983). This method is widely used in literature but typically extends to the analysis of the effects of specific events or occurrences on financial or economic outcomes (Halpern 1983). The process involves comparing the outcome of interest before and after the event, in order to understand how the event has affected the outcome. Event studies are often used as a descriptive tool, to understand the dynamics of the outcome of interest before and after the event and to identify any changes that may have occurred as a result of the event. For the purposes of this study, the event study approach was chosen as it is a widely used and powerful tool that would facilitate the identification and measurement of the impact of *digital acquisitions* on a firm's *digital capabilities*.

To investigate the effects of digital acquisitions on digital capabilities, we collected data on the number of completed digital acquisition deals for each firm, over a given time period, as well as data on the level of digital capabilities for each firm across the same period. Applying methodology from prior research, we implemented a firm's filing of digital patents as a proxy for its digital capabilities (Hanelt et al., 2021). We further employed panel data to track changes in our variables of interest over time, and across different entities, to identify correlations and relationships between the variables. Panel data refers to a type of longitudinal set of data that involves collecting data from the same individuals or groups over an extended period of time (Bryman & Bell, 2017). It was implemented as it could be tested to see whether or not, and how strongly, variables are related (Hair et al., 2018).

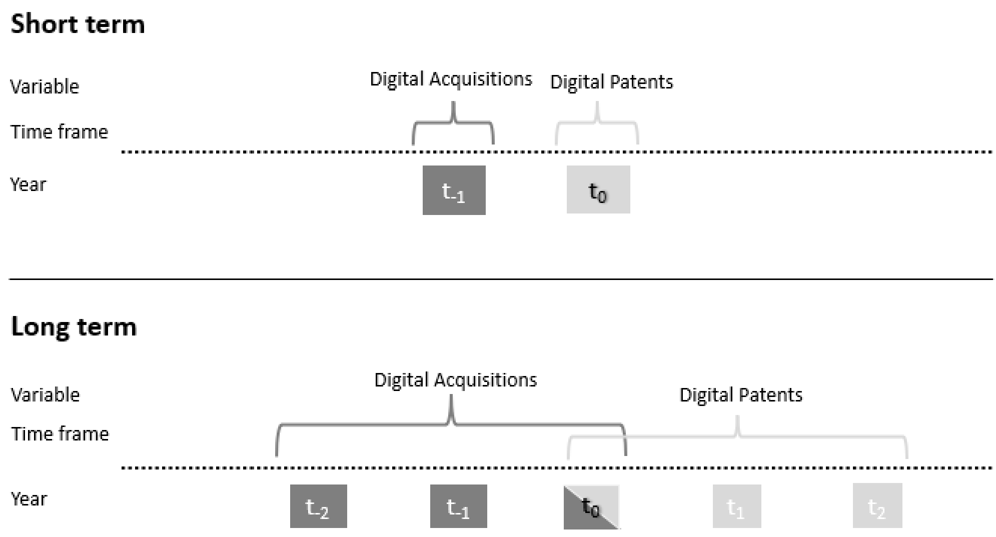

Figure 1. Event study time frame for short and long term models.

Additionally, we chose to examine digital acquisitions from two different time frames: a short-term period immediately following the acquisition, and a longer-term period that extended the time frame, providing an overview over a longer duration. This decision was based on prior research that has used similar time frames (Hanelt et al. 2021). By looking at both short-term and long-term effects, however, we sought to gain a more comprehensive understanding of how the acquisitions affected a firm's digital capabilities, thereby contributing to the existing research. An overview of the short-term and long-term models can be seen in Figure 1. In the short term model, we look at the digital capabilities of a firm at t_0 following the acquisition of a digital firm one year prior, t_{-1}. In the long term model, we look at the cumulative amount of acquisitions that have occurred between t_{-2} and t_0 and examine how they relate to a firm's cumulative digital capabilities between t_0 to t_2. Other relevant performance metrics for each individual firm before, during and after the acquisition event were also collected and included as control variables. A two-way fixed effect regression model was then conducted to analyse whether digital acquisitions had a significant effect on the firm's digital capabilities, controlling for factors that may have affected the outcome of the study, such as time and entity fixed effects.

To test our hypothesis, hypothesis testing was conducted to examine the relationship between the independent and dependent variables. The acceptance threshold for all statistical tests in this study was set at 5% ($\alpha = 0.05$).

3.2.1. Scope and boundaries of the study

Delimitations are an important part of the research process, as they help to ensure that the research is focused and manageable and that the results can be accurately interpreted and generalized (Bryman & Bell, 2017). Specifying the delimitations of the research was thereby vital in ensuring that their study is feasible and that the results will be relevant and meaningful. Defining the scope and boundaries of the study ensured a more focused research process. The delimitations chosen for this study can be summarized as follows:

Time frame: The study is limited to a specific time frame, covering the years 2010-2021. This was done to ensure that there was sufficient data for an effective statistical analysis. By collecting data from the individual firms over multiple years, rather than just one year, it was possible to gather and process a larger, and more robust, data set.

Possessing a data set that spans multiple years allowed for the examination of trends and changes over time, which provided valuable insights into the factors that are driving the outcomes of digital capabilities. Additionally, having more data points helped increase the statistical power of the analysis, facilitating the process of detecting meaningful differences or relationships between variables.

Most importantly, the exact choice of years has been chosen to match and reflect the rise of digital capabilities within the industry (Stewart et al., 2018).

Scope of sample: The study is focused on electric utility firms. For the purposes of this study, we chose to focus on a specific industry - the energy utilities sector - in large part due to it being a traditionally non-digital industry. Furthermore, its potential to be contrasted with previous studies within the digital capabilities research framework provides a foundation in which comparable results may be analysed and interpreted.

The energy utilities industry has been facing significant pressure to digitalize over recent years, and as a result, firms within this sector have been pressured to incorporate digital innovation into their operations in order to remain competitive (Stewart et al., 2018). By focusing on a single industry, we are able to examine the ways in which companies are responding to the pressure to digitalize and how they are implementing digital capabilities in a more controlled setting

Hanelt et al (2021). studied the industrial industry, looking at automotive firms, to explore the impact of digitalization within the industry. Similarly, the electric utility industry has been impacted by digitization in its various business processes. The adoption of such digital technologies has however not progressed at the same rate in both sectors (Kiesling, 2016). This may be due to a variety of factors, such as the differing nature of the products or services offered by each industry, the level of competition, or the regulatory environment in which each industry operates. Specifically, the utility sector has been shown to be slower to adopt digital technologies compared to other industries, potentially due to its conservative nature and the presence of natural monopolies that are government-owned or heavily regulated (Stewart et al., 2018). These factors may limit the ability of entrepreneurs to disrupt traditional business supply chains and promote digital transformation in the sector. As a result, the utility sector has lagged behind other industries in its adoption of digital technologies and has yet to fully experience the transformative power of digital disruption to the same extent (Stewart et al., 2018). It is also possible that the electric utility industry has faced other unique challenges or barriers that have slowed its adoption of digital technologies. It remains therefore to examine whether the results for the electric utilities industry are comparable to that of prior research given that the electric utility industry has been slow to embrace digitalization but now finds itself in a spot much akin to that of the industries examined in earlier studies.

Sites selection: The study is limited to two geographic regions: North America and Europe. Conducting a study that spans many geographic regions can be resource-intensive in terms of time, and work. Thus, we limited the scope of the study to just two regions, to better manage the limited time we had.

Homogeneity of the sample was also considered when choosing North America and Europe. We chose them because we found them to be sufficiently similar in terms of relevant cultural, economic, and political factors, and therefore would be appropriate to include in the same study. By including both regions we also helped to somewhat expand our sample size for the study. Finally, the choice of North America and Europe had been a practical one, as we had access to data sources that made it easier to conduct the study for these regions.

3.3. Measures

When devising measures for research concepts, it is important to select measures that are appropriate and suitable for the specific research context. Bryman and Bell (2017) stress the importance of the process of operationalization, the act of turning abstract concepts into measurable observations, to ensure their reliability, validity, and sensitivity to the concept being studied. Choosing appropriate measures for research concepts is a critical step in the research process. By selecting measures that are reliable, valid, and sensitive to the concept being studied, one ensures that the findings are accurate and meaningful.

In the following subsections, we provide descriptions of our main variables, as well as an explanation of how they were operationalized and measured, followed by a discussion of the control variables. A complete list of all variables used in this study, along with their definitions, operationalization, and data sources, can be found in Appendix 9.1.

3.3.1. Dependent variable: Digital capabilities

Previous research has used patents as a proxy for technological capabilities (Piirainen, Tanner & Alkærsig, 2017). Accordingly, we implement patents as a measure of a firm's digital capabilities as it has been shown to be a consistent and reliable measure. Hanelt et al. (2021) showed that patents can act as a mediator between digital M&As and digital innovation. Digital capabilities are defined as "A firm's skill, talent, and expertise to manage digital technologies for new product development" (Khin & Ho, 2018, p.182).

3.3.2. Independent variable: Digital acquisitions

The independent variable also known as the predictor or explanatory variable is a variable that is hypothesized to affect the dependent variable. The purpose of the independent variable is to help explain or predict the values of the dependent variable (Bryman & Bell, 2017).

Previous studies have suggested that digital acquisitions can lead to an increase in digital capabilities (Hanelt et al., 2021; Tang, Fang & Jiang, 2022). Thus, we investigate the effect of digital acquisitions, as an independent variable, on the dependent variable, the number of digital patents filed. Following other studies in the research field, we defined digital acquisitions as *Acquisitions of firms that intensely leverage digital technologies* (Hanelt et al., 2021).

3.3.3. Control variables

Control variables, also known as covariates or confounding variables, are variables that have been included in a regression model in order to control for the effects of other variables that might confound the relationship between the predictor and outcome variables (Hair et al., 2018). In a regression model, control variables can be used to prevent omitted-variable bias, which occurs when important predictor variables are not included in the model.

Omitted-variable bias can lead to inaccurate and misleading results, as it can cause the estimates of the model parameters to be biased or inconsistent. This can happen when an omitted variable is correlated with both the predictor and outcome variables, as it can affect the relationship between these variables and distort the results of the analysis (Hair et al., 2018).

By including control variables in the model, we controlled for the effects of these other variables and reduced the risk of omitted-variable bias. This helped to improve the accuracy and reliability of the results, and provided a more nuanced and comprehensive understanding of the relationships between the variables being analysed.

3.4. Sampling method

The sample of companies included in this study was gathered from the S&P index of the 250 largest energy firms in the world (S&P Global, n.d.). In order for a firm to be eligible for inclusion, it had to meet the following criteria: 1) it must be an electric utility firm, 2) it must be based in North America or Europe, 3) it must have been operational throughout the entire study timeframe, and 4) it must not have been acquired by another company. These inclusion and exclusion criteria were used to ensure that the sample was a fair reflection of the larger population of energy utility companies. This procedure was also conducted such that a manageable data set could be procured, considering the time restrictions of the study.

The sample of companies included in this study was selected based on specific criteria, implying that the selection process was not completely random. As a result, it is possible that the sample may be biased in some way and the results of the study may not be fully representative of the larger population of energy utility firms. For instance, previous research has shown that companies with stronger digital capabilities tend to have better financial performance (Hanelt et al., 2021). Therefore, by studying the current largest energy utilities firms, we may be focusing on companies that have had successful digital acquisitions and have subsequently developed stronger digital capabilities. This could potentially impact the results of the study, as we would be examining a group of firms that may have already achieved success in terms of digitalization and financial performance. To mitigate this potential bias, we chose to focus specifically on the largest energy utilities firms as of 2010, which is the start of the set time frame for this study. By selecting firms that had, or were in the process of, digitization we hoped to be able to capture the firms that have undergone both successful and failed digital acquisitions, thereby minimizing the impact of any potential bias, to ensure that the results of the study accurately reflect the situation.

3.5. Data collection

In this study we sought to examine the correlation between digital acquisitions and digital capabilities. To collect the data for the analysis a variety of secondary sources were used.

Secondary analysis, which refers to the use of existing data for a new research purpose, can be a valuable alternative to collecting new data in certain situations (Bryman & Bell, 2017). There are several advantages to considering secondary analysis. One advantage of secondary analysis is that it can be more time-effective than collecting new data. Data collection is a time-consuming and expensive process, and conducting a secondary analysis better leverages the resources and efforts of previous studies and existing databases. This was particularly useful given the limited time as it immensely accelerated the data collection process.

Another advantage of secondary analysis was that it could provide access to larger and more diverse samples than what might be possible to collect through manual collection. Existing datasets may include data from a wide range of individuals or organizations, which can provide valuable insights that might not be obtainable with a smaller, more homogenous sample. Similarly, databases may have access to specific information sources that are not as easily obtainable by single individuals.

The choice of secondary data is also greatly beneficial in panel data. The ability to include a large number of cross-sectional units and time periods while also integrating the analytical capabilities of regression for explanatory purposes makes panel models a suitable match for the usage of secondary data (Bryman & Bell, 2017).

The data values procured in the study were based on the acquirer in the *Acquisition process*. In most acquisition deals, acquiring leads to a complete absorption of the target firm and, therefore, the data on the target company would no longer be publicly available. Because the effect of acquisitions on digital capabilities can depend on the relative positions of the acquirer or target firm, it is appropriate to look at the acquirer's data in order to consider its significance.

3.5.1. Digital patents - Dependent variable

To collect data about digital patents the *espacenet* service was used. The service is provided by the European Patent Office, and it covers most of the patents published in the world (espacenet, n.d.). Since each firm files potentially thousands of patents in a single year, a manual evaluation of every patent was not feasible. Thus, we extracted all potential digital patents by performing a keyword search. The keywords adopted in this study are displayed in Appendix 9.2.. In the keyword search, we filtered patents to include those that contained at least one of the keywords in our search query in either the patent description or title. The patents were also filtered by publishing date, viewing only patents published in 2010 or later since the study only would include patents with a priority date between 2010 and 2021. Next, we manually went through all the remaining patents to decide whether they were digital or not. This part was done by reading the abstract, patent claim(s) and or description for each patent. If any of the sections provided enough information to mark the patent as digital, the remaining sections were not read. If a patent was written in a language other than English or Swedish the patent was translated using *google translate* or *espacenets* own translation feature. For each patent, three data points were collected: the priority date; the priority number and the patent applicant.

Our method for collecting data for the number of patents, although similar to that of Hanelt et al. (2021), also accounted for a more in depth overview of digital patents as we also looked at the number of digital patents issued by the 5 largest subsidiaries of each firm. To our knowledge, this has not been considered in prior studies when implementing patents as a measure for digitalization capabilities.

3.5.2. Digital acquisitions - Independent variable

To gather information about the digital acquisitions of the firms in our sample, Thomson Reuters Eikon's screener function was used (Refinitiv Eikon, n.d.). The settings applied in the acquisition search query are shown in Appendix 9.3. We collected information of all acquisitions that took place within the scope of our study 2010-2021 for each of the firms in the sample. In particular, we also included each, looking at not only deals in which the acquiring firm was the direct acquirer but also where it was an intermediate and ultimate acquirer. The result of this was that we were also able to collect data on acquisitions for each of the acquiring firm's subsidiaries and sub-subsidiaries. This helped to ensure that the firms that handled most of the acquisitions through a subsidiary also were fairly represented in the data set.

Each acquisition was then manually inspected to determine whether or not it was considered a digital acquisition or not. The variables *Target Macro Industry* and *Deal Synopsis* were used as primary decision-making benchmarks, as they provided the most beneficial information in regards to identifying whether an acquisition would be considered digital. If these were not sufficient, other sources of information were retrieved to guide the classification. Sources such as company websites and news articles were manually inspected to judge whether the target was to be considered a digital acquisition.

A complication was that it was not possible to directly infer whether a deal was a merger or an acquisition using the database. Thus, we restricted ourselves by carefully looking at acquisitions in which the deal did not result in the creation of a new firm but rather an absorption of a firm being acquired.

3.5.3. Control variables

The data for control variables were collected from the Eikon database using the *function builder* tool (Eikon n.d.). We encountered some issues during the data collection process, however. For certain values, Eikon did not have the necessary data available. To address this, we manually gathered the missing data, using officially published financial reports such as annual reports from individual firms to fill in and amend the missing data values. Moreover, for the sake of consistency in the data set, we ensured that all values were collected in USD

($), manually converting local currencies when appropriate while also taking into account the exchange rate in different time periods.

During our initial ocular review of the dataset, we noticed certain values that seemed abnormal or out of place. To ensure the quality and accuracy of our data, we conducted a thorough investigation using data visualization tools to identify any potential issues or discrepancies in the data set. Any data points that stood out or seemed unusual were taken and compared with their respective original source materials to verify their accuracy. We found that the data obtained from Eikon had on many occasions misinterpreted values in the financial documents, such as not properly differentiating when values in annual reports were presented in thousands, millions or billions. For these values, it was possible to identify that they were scaled up or down by a factor of 1000 as there was a visible discrepancy in the magnitude of the data values. At other times it was clear that the data from Eikon had taken values incorrectly from the financial documents as it was possible to see that their data at times reflected the wrong measure. Thus, we found it necessary to be careful when adopting the data for our control variables.

3.6. Regression model

The research model specifications are an important part of any research study, as they determine the accuracy and reliability of the research findings (Bryman & Bell, 2017). By carefully specifying the details of the statistical model, it is possible to ensure that the model accurately reflects the data and the research question being studied. This can help to ensure the validity and reliability of the research findings and can assist in drawing more accurate conclusions (Bryman & Bell, 2017).

3.6.1. Two-way Fixed effects regression

One effective way of analysing panel data is to use fixed effects regression. Ordinary Least Squares (OLS) regression is a commonly adopted statistical method for analyzing the relationship between a dependent variable and one or more independent variables (Hair et al., 2018). However, when working with panel data, OLS can be problematic because it does not adequately account for the fact that there may be significant differences between entities. For example, when studying the effect of digital acquisitions on a firm's digital capabilities, the overall trend across all firms might be negative. In this case, OLS would not be able to accurately capture the true effect of digital acquisitions on individual firms, as it would be confounded by the negative overall trend.

Similarly, larger firms may have a higher level of initial digital capabilities compared to smaller firms. This means that when using OLS to analyse the relationship between digital acquisitions and digital capabilities, the results may be biased because they do not account for the fact that larger firms may have a higher digital capability prior to an acquisition.

To properly observe the true effect of digital acquisitions on digital capabilities, it is, therefore, necessary to eliminate the across-entity variation. This can be done using fixed effects regression, which considers the multidimensional nature of panel data and accounts for the time-invariable individual characteristics of the firms being studied (Hair et al. 2018). Entity fixed effects refer to the effect of inherent differences between individual entities, such as companies or individuals, on the outcome of the study. Fixed effects regression has thus been chosen for the purposes of this study as it provides a more appropriate method for analyzing panel data and can yield more accurate results when compared to OLS.

Following the studies of Hanelt et al. (2021) and Tang, Fang & Jiang (2022) we have further chosen to include time fixed effects in addition to the entity fixed effects. In general, time fixed effects refer to the effects of time-varying factors that are not dependent on the entity, such as seasonality or overall economic conditions, on the outcome of the study. Time-fixed effects help to account for changes in the overall environment or in the contexts in which the firms are operating. Changes in for instance economic conditions, technological advancements, or regulatory changes can all affect the relationship between the independent and dependent variables. By including time-fixed effects, it was possible to control for these changes and to better isolate the effect of the independent variable on the dependent variable.

One theoretical approach of creating a two-way fixed effect model is through the use of demeaning (Williams, 2015). Demeaning refers to the process of subtracting the mean value of a variable from each data point in the sample. This is done to centre the data around zero, which can make the results of the regression easier to interpret. Demeaning can be useful when working with panel data, where the same group of individuals or organizations is being observed over time. By demeaning the data, the mean values for each group are removed, allowing the analysis to focus on within-group changes over time rather than between-group differences. For a two-way fixed effects regression demeaning can be done through the following steps:

Assuming a regression model (1)

$$y_{it} = u_i + \nu_t + \beta X_{it} + e_{it} \quad (1)$$

Where i is the entity (firm) and t is time. The time fixed effect, u_i, and the entity fixed effect, v_t, determine the intercept. The error term is u_{it} and β is a coefficient.

Demean the model cross-sectionally for each entity, i, giving (2)

$$\bar{y_i} = u_i + \bar{v} + \beta \bar{X_i} + \bar{e_i} \quad (2)$$

Subtracting models (1) – (2), resulting in (3)

$$y_{it} - \bar{y_i} = \nu_t - \bar{v} + \beta(X_{it} - \bar{X_i}) + (e_{it} - \bar{e_i}) \quad (3)$$

Demean (1) for each time interval, t, giving (4)

$$\bar{y}_t = \bar{u} + \nu_t + \beta \bar{X}_t + \bar{e_t} \quad (4)$$

Subtracting equation (4) from (3)

$$y_{it} - \bar{y_i} - \bar{y_t} = \beta(X_{it} - \bar{X}_i - \bar{X}_t) - (\bar{v} + \bar{u}) + (e_{it} - \bar{e}_i - \bar{e}_t) \quad (5)$$

Thereby, in equation (5), the entity fixed effects and time fixed effects have subsequently been removed.

3.6.2. Regression model specification

The general two-ways fixed effects regression model implemented for this study is depicted in the equation below:

$$Y_{i,t} = \beta_0 X_{it} + \beta_1 C^1_{it} + \beta_2 C^2_{it} \ldots + \beta_7 C^6_{it} + u_i + v_t + e_{it}$$

Where Y_{it} is the number of digital patents for a company, *i,* in year *t*. X_{it} the number of digital acquisitions and C^1_{it} to C^6_{it} are the control variables. The equation also contains the error term e_{it}, the time fixed effect, u_i, and the entity fixed effect, v_t, the last two determine the intercept.

3.6.3. Assumptions of fixed-effects model

A fixed effects regression model makes several assumptions about the nature of the data and the relationships between the variables being analysed. The key assumptions that are made in a fixed effects regression model are:

The error term has a conditional mean of zero: This assumption states that the error term in the model is uncorrelated with the predictor variables, on average. This is necessary in order for the estimates of the model parameters to be unbiased.

Large outliers are unlikely: This assumption implies that extreme values in the data are unlikely to occur, or that they will have a minimal impact on the estimates of the model parameters.

Independent and identically distributed (i.i.d) variable draws from a joint distribution: This assumption states that the independent variable in the model is independently and identically distributed (i.i.d.) for each year, implying that they are drawn from a common joint distribution.

There is no perfect multicollinearity: This assumption states that there is no perfect multicollinearity in the model, which means that the predictor variables are not perfectly correlated with one another. Multicollinearity can lead to unstable and inconsistent estimates of the model parameters, which can affect the accuracy and reliability of the results.

3.6.4. Statistical tests

To assess the assumptions of the model, statistical tests were used to evaluate whether the assumptions of the fixed effects regression model were met.

Variance Inflation Factor (VIF): The VIF measure is used to assess the degree of multicollinearity in a regression model. Multicollinearity occurs when two or more predictor variables in the model are highly correlated with each other. This can lead to unstable and inconsistent estimates of the model parameters, which can affect the accuracy and reliability of the results. VIF values below 5 are generally considered to indicate that multicollinearity is not present in the data set and has subsequently been chosen for this study.

Hausman test: The Hausman test is used to assess the presence of endogeneity in a regression model. Endogeneity occurs when the error term in the model is correlated with one or more of the predictor variables. This can lead to biased estimates of the model parameters, and it can be difficult to accurately interpret the results. The Hausman test compares the results of two different regression models, and it is used to determine whether one model is preferred over the other based on the assumption of endogeneity. In panel data analysis, the Hausman test provides a foundation to support the decision of choosing between fixed effects model and a random effects model (Hair et al., 2018).

Heteroskedasticity test: One potential issue that can arise in regression analysis is heteroskedasticity, which refers to non-constant variance in the errors of the model. According to Feng et al. (2020), there is a lack of research on the heteroskedasticity of fixed effects models, and therefore there is no readily available test to assess this issue in the current study. As an alternative, we can plot the residuals of the regression model to examine the fit of the model.

3.7. Statistical software: R

In this study, the programming language R was utilized to perform various data manipulation and statistical tasks, including regression analysis and statistical tests. R has a wide variety of packages available that provide additional functionalities. A list of the packages used can be found in Appendix 9.5 along with descriptions of their functionalities. The primary packages that were used in this study are the following:

The *plm* package in R is a suite of functions for fitting and comparing panel data models and provides tools for fitting a variety of panel data models in R. In addition to fitting panel data models, the “plm” package also provides functions for diagnostics, prediction, and visualization of panel data models (Croissant & Millo, 2008).

The *tidyverse* is a collection of R packages that are designed to work together for data manipulation and visualization. The packages in the tidyverse are built on the principles of "tidy data", which refers to a standardized way of organizing data values within a dataset. The goal of the tidyverse is to provide a consistent interface for working with data in R, making it easy to manipulate, visualize, and model data (Wickham et al., 2019).

3.8. Method discussion

In this section additional commentary regarding the research design, the sample, the data collection and analysis procedures, and any other relevant details about the study is provided. This information is critical for establishing the validity, reliability, and transparency of the results, and it also helps to facilitate the replication of the study by other researchers. Potential limitations or biases in the study are also presented.

3.8.1. Reliability

Reliability refers to the consistency and stability of a study. A reliable study is one that produces consistent results over time and across different measurement occasions (Bryman & Bell, 2017). In order to ensure reliability, the measures that have been tested and shown to be reliable in previous studies have been selected. A consistent method and procedure process have been implemented throughout the study, as it reduces the chance of measurement error thereby increasing reliability of the results.

An improvement would have been to use multiple measures of the same concept, as the reliability of the study can be increased because the results are less likely to be affected by random error. Furthermore, adopting more data from a larger range of sources would help to triangulate the results and provide a higher level of confidence in the findings. Furthermore a Cronbach Alpha test, measuring the internal consistency of tests and measures thought of being used, but ultimately was not included in the study due to time constraints..

3.8.2. Validity

Validity refers to the accuracy and relevance of a measure (Bryman & Bell, 2017). A valid measure is one that accurately reflects the concept being studied and provides meaningful information about the research topic. In order to ensure validity, it was critical to carefully consider the operationalization of the concepts being studied and choose measures that capture the important aspects of the construct. Thus we were careful in implementing measures such that they measure the concept it is intended to measure, but also to ensure that the results of a study can be attributed to the independent variable being studied. The operationalization of measures can be found in Appendix 9.1.

3.8.3. Limitations

Despite the use of a quantitative approach having a number of benefits, including the ability to analyze large amounts of data, to use rigorous statistical methods to test hypotheses, and to generalize findings to a larger population. There are limitations to this approach that should be considered.

A limitation of a quantitative approach is that it may not always be possible to capture the complexity and nuance of real-world phenomena. In many cases, research questions may be too complex or multifaceted to be fully captured by quantitative measures and statistical models. Additionally, the use of standardized instruments and measures may not always be appropriate for capturing the unique characteristics of different situations or contexts. For the purposes of this study, patents have been selected as a measure of digital capabilities, providing insight into the level and quality of the capabilities that are taking place in a firm. However, it is important to recognize that patents are not the only measure of capabilities and that other factors, such as the adoption of new technologies and the launch of innovative products and services should also be considered when evaluating the level of digital capabilities in the firm. Unfortunately, due to the time constraints of the study, it was not possible to examine these other factors and their impact on digital capabilities. This limitation may impact the generalizability of the findings and could be addressed in future research by extending the scope of the study to include additional dependent variables as well as a broader selection of geographic regions.

Another limitation of a quantitative approach is that it may be more difficult to identify the underlying mechanisms or processes that are driving the relationships between variables. While statistical models can provide insights into the relationships between variables, they may not always be able to fully explain the underlying causes of these relationships. For instance, another way to use patents as a measure of digital capabilities would be to look at the quality and impact of the patents that are filed. This could involve evaluating the novelty and usefulness of the patented inventions, as well as their impact on the industry and on society more broadly. By looking at the quality and impact of patents, it would be possible to capture a more nuanced understanding of the level of capabilities in the firm. Given the time constraints for this study, however, we were unable to conduct such an extensive investigation.

Another limitation was that we looked at data on a year-to-year basis. Due to our control variables exclusively being measured at one-year intervals, it was not possible to provide a framework in which a more detailed analysis of the effects between each year could be identified. Having a more continuous set of data could potentially increase the overall accuracy of the models and in doing so, improve our overall understanding.

4. Results

In this chapter a comprehensive overview of the data set in the form of descriptive statistics is presented. This is then followed by the results from the two-way fixed effects regression along with the results from the statistical tests. The regression results are presented along with a table visualising the time periods of the presented tests.

4.1. Descriptive statistics

In this study, we analysed panel data collected from 29 electric utility firms over a period of 12 years. Descriptive statistics were calculated by looking at all variables at each and every time point (yearly). Across the entire sample, there were a total of 236 total digital patents filed, with an average of 8.14 digital patents filed per firm. While our entire sample includes a total of 29 firms, there were only 33 completed digital acquisition deals over the course of the study period. This implies that the average firm in our sample made 1.14 digital acquisitions across the data set. This relatively low number of digital acquisitions may potentially impact the results of our study, as it suggests that potentially a small number of firms are responsible for the majority of the digital acquisitions that occurred. This could potentially skew the results, as the relationship between digital acquisitions and other variables may be influenced by the characteristics of these firms.

The mean logarithmized (ln) size of the firms in the sample across all years was found to be 23.166, with a standard deviation of 1.038. A comprehensive list of each variable along with their respective mean, median, standard deviation, and max and min values can be seen in Table 1.

Table 1. Shows descriptive statistics, such as the mean and median, of the variables used in the two regression models.

Variable	Obs.	Mean	Median	Std. Dev.	Max	Min
Short term						
# Digital Patents, y_0	319	0.708	0	1.954	16	0
# Digital Acquisitions, x_{-1}	319	0.103	0	0.410	3	0
Long term						
# Digital Patents, y_0-y_3	232	2.366	0	5.321	30	0
# Digital Acquisitions, x_{-3}-x_0	232	0.297	0	0.807	5	0
Control variable						
Log (Size)	348	23.166	23.019	1.038	25.884	21.349
Leverage (%)	348	0.323	0.318	0.113	0.594	0.099
Profit Margin (%)	348	0.158	0.135	0.148	0.668	-0.416
Liquidity (%)	348	0.029	0.019	0.029	0.165	0.000
Capital expenditure (%)	348	0.212	0.177	0.163	1.703	0.009
Log (Capital intensity)	348	14.171	14.244	0.764	16.025	12.223
Revenue Growth (%)	348	0.033	0.005	0.495	8.804	-0.878

One discovery from the descriptive statistics is that the median number of digital acquisitions and the median number of digital patents for our sample of firms is 0, for both the short term and long term models. Given that the data is in a panel format, this suggests that firms in our sample on more than half of the observations did not engage in any digital acquisitions nor performed any digital patents filings. This is however not surprising considering that the study uses panel data, and thus observed not solely how many digital acquisitions each firm made but also how many are made across each year across the entire 12-year period. Observing a median value of 1 would subsequently imply that the firms on average underwent 1 or more digital acquisitions per year for at least 6 years throughout the 12 years period. Nonetheless, the finding is an important consideration in regard to the regression because it may indicate that the distribution of digital acquisition activity is skewed, with a small number of firms engaging in a large number of acquisitions, while the majority of firms have not engaged in any acquisitions at all.

Skewed data could have a number of implications for the analysis and interpretation of the results. For example, it may be difficult to draw conclusions about the relationship between digital acquisitions and other variables based on the mean value, since the mean can be influenced by extreme values at the high or low end of the distribution. Instead, it may be more appropriate to use other measures of central tendencies, such as the median, to describe the distribution of the data.

Additionally, skewed data may indicate that there are underlying factors that are driving the patterns in the data, such as differences in the size, industry, or strategic focus of the firms in the sample. It is important to consider these factors as the analysis and interpretation of the results and to consider whether they may be influencing the relationship between digital acquisitions and other variables.

The panel data revealed a generally consistent pattern of characteristics for the firms over time. In particular, a positive trend for both the number of digital acquisitions and the number of digital patents filed per year could be observed, as can be seen in Figure 2 and Figure 3. However, we noticed a sharp sudden downturn for both variables between 2020-2021, which may have contributed to the relatively low R-squared value for the linear trend line approximation in the figures.

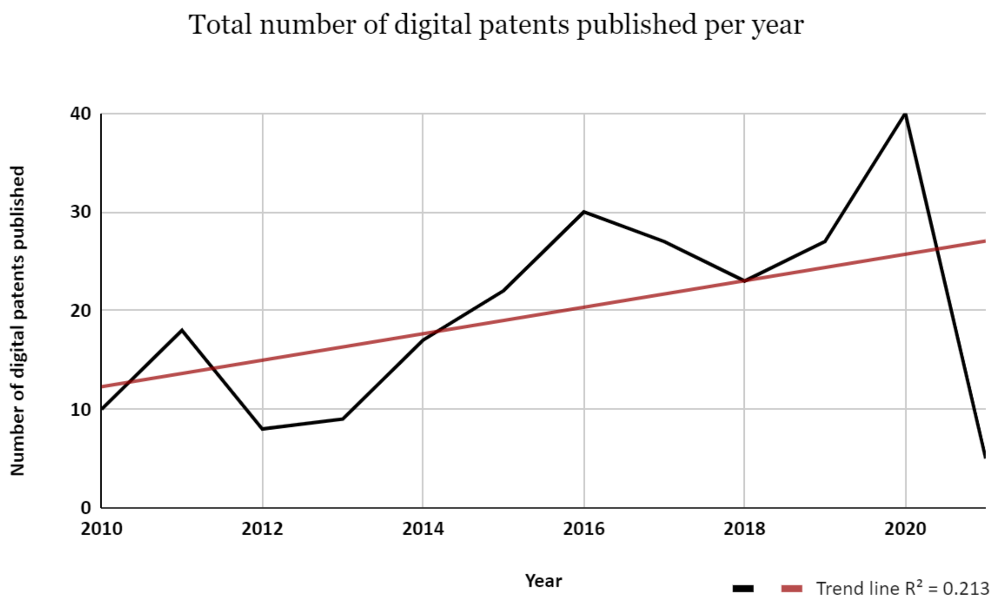

Figure 2. Shows the total number of digital patents published per year, in the sample. The R^2 value of the trend line is 0.213.

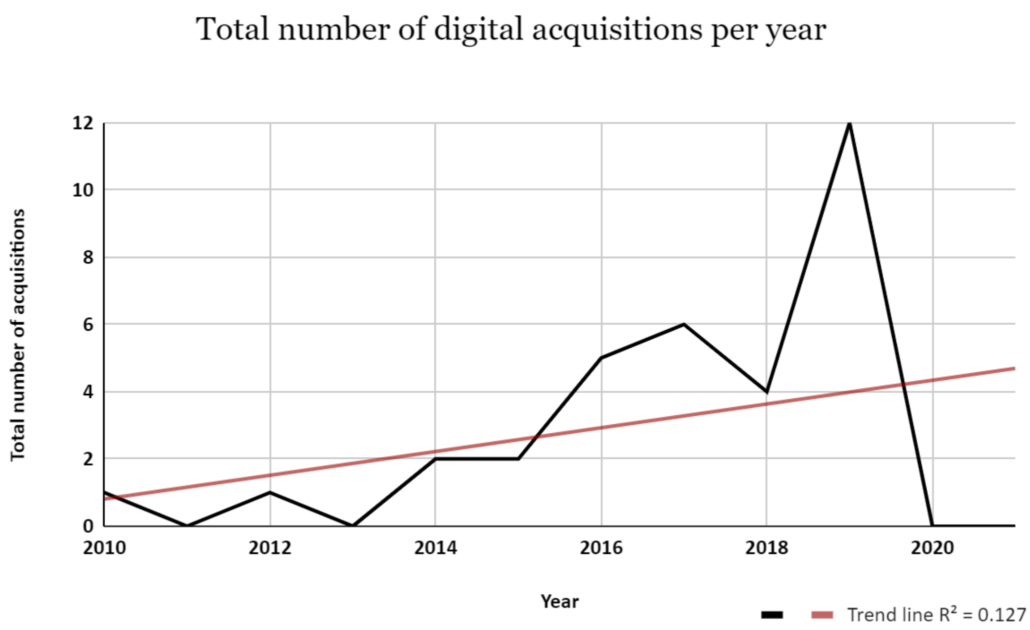

Figure 3. Shows the total number of digital acquisitions per year, in the sample. The R^2 value of the trend line is 0.127.

It is worth noting that the R-squared value for a linear approximation in the figures is low, but it does not necessarily indicate a lack of relationship between the variables. It simply means that the linear trend line is not a particularly good fit for the data and that other factors may be influencing the observed trends. Thus, further analysis will be needed to understand the reasons behind the decrease in digital acquisitions and patents in 2020-2021 and to determine whether this represents a temporary dip or a longer-term shift in the data. We suspect however that the results may have been partially influenced by the Covid-19 pandemic, which occurred in 2020. The pandemic may have had a variety of impacts on firms' digital acquisition activities as certain firms may have had to scale back their digital acquisition efforts due to financial constraints or disruptions to their operations. Further research into the topic would be necessary to determine whether this is the case.

The majority of the electric utility firms in the sample are located in Europe 68.97%, with the remaining located in North America 31.03%. In terms of firm size, the seven largest firms in the sample in the year 2021 contributed 72.5% of the total patents filed across the entire data set, with the rest only contributing 27.5%, as illustrated by Figure 4. Looking at the proportion of the total digital acquisitions for the same seven firms on the other hand, we find that they only account for 63.6% of all digital acquisitions, as can be seen in Figure 5.

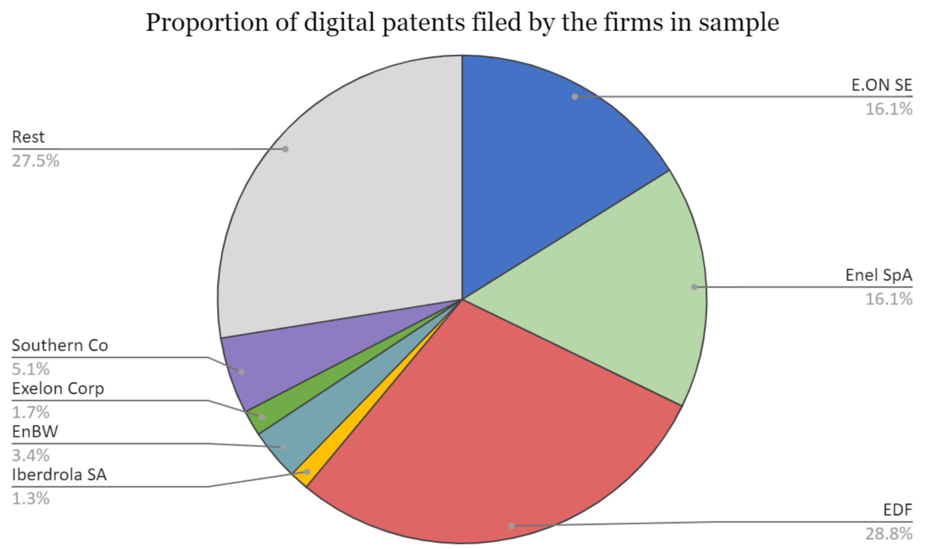

Figure 4. Distribution of the published digital patents in the sample. E.ON SE, Enel SpA and EDF publish a majority of the digital patents in the sample.

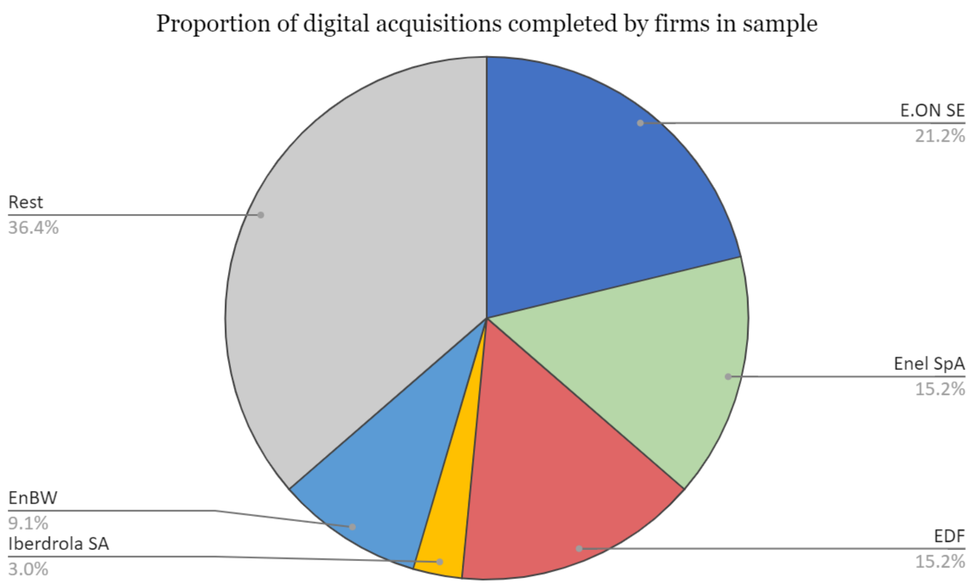

Figure 5. Distribution of digital acquisitions in the sample, E.ON SE, Enel SpA and EDF make out a small majority of the completed digital acquisitions.

In summary, the descriptive statistics for our sample of firms indicate that the firms in our sample on average engaged in at least one digital acquisition in the past twelve years and that the number of digital patents filed by these firms, with an average of 8.13 digital patents per firm, has increased over time. However, there are also a significant number of firms that have not engaged in any digital acquisitions, and a small number of firms that have not filed a single digital patent across the 12 years. These findings suggest that there is considerable variability in the digital acquisition and patent filing activities of the firms in our sample, and should be considered when concluding the analysis.

4.2. Regression results

To test the hypothesis described in section 2.3, two-ways fixed effects regression models were tested for the short- and long term model. The time frame for each of these models are represented in Table 2.

Table 2: Shows the time frame of the two models. The independent variable (digital acquisitions) is tinted dark grey while the dependent variable (digital patents) is tinted light grey.

Model	Time-period for independent and dependent variable				
Short		t_{-1}	t_0		
Long	t_{-2}	t_{-1}	t_0	t_1	t_2

The regression results, seen in Table 3, show a statistically significant result at the $p < .01$ level, for the independent variable digital acquisition, for both the short and long term model. The R-squared adjusted value takes the number of predictors into account and thus gives a smaller value than the regular R-squared value. All R-squared values are higher for the long term model than the short term test. The long term model also shows a lower ANOVA p-value, albeit with an overall lower number of observations, 232 vs 319 observations.

Table 3. Shows the results from two-way time and entity fixed effects regression tests. ***, **,* and ., indicate significance at the 0.1%, 1%, 5% and 10% levels.

Variable	Model	
	Short term	Long term
Digital Acquisitions	**0.617** (0.007)**	**-0.906** (0.006)**
Revenue	-0.752. (0.059)	-5.247*** (0.000)
Leverage	3.530* (0.041)	8.284. (0.082)
Profit Margin	1.224 (0.244)	3.351 (0.171)
Liquidity	1.947 (0.664)	11.720 (0.295)
Capex	0.265 (0.845)	2.640 (0.509)
Capital intensity	-0.754. (0.058)	-1.504 (0.124)
Revenue Growth	0.525** (0.010)	3.614* (0.035)
R-Squared Within	0.080	0.152
R-Squared	0.558	0.799
R-Squared Adj	0.484	0.753
ANOVA p-value	0.00361	0.000121
Time fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
N	319	232

4.3. Results from statistical tests

In addition to our main results, we also conducted various robustness tests to ensure that our findings were robust and reliable.

Table 4. Shows the Hausman p-value for both models. The Hausman p-value was significant for both models, fixed-effects regression was therefore chosen instead of random effects.

Time frame	Short	Long
Hausman p-value	0.0076	2.044e-11

To effectively analyse panel data using regression, the appropriate regression model type should be chosen. To confirm which was more appropriate between a random effects and fixed effects model, a Hausman test was performed on both the short term and long term models. The Hausman test showed a significant p-value for both tests, see Appendix 9.3, and thus the fixed effects regression was chosen. The null hypothesis in the Hausman test is that the preferred model is a random effects model, while the alternative hypothesis is that the preferred model is a fixed effects model. It was thereby concluded that the fixed effects model was preferred.

Table 5. Shows the VIF value for each independent and control variable, for each model. For example, the VIF value for the control variable *Revenue* is 1.37 for the test with y_1 as dependent and x_{t2} as independent.

Variable	Model	
	Short (VIF)	Long (VIF)
Digital Acquisitions	**1.08**	**1.17**
Size	1.33	1.35
Leverage	1.73	1.85
Profit margin	2.05	2.42
Liquidity	1.23	1.24
Capex	2.15	2.23
Capital intensity	1.84	1.84
Revenue growth	1.02	1.06

The VIF values for the independent and control variables were calculated to explore whether there was multicollinearity in the data set. All values were found to be below three, indicating a fairly low level of multicollinearity, as depicted in Table 5.

5. Analysis

In this chapter the findings of the study are presented and discussed. First, the result of the two-way regression is analysed based on the purpose, research question and research hypothesis. Secondly, the short and long term effects of digital acquisitions on digital capabilities are analysed and compared.

5.1. Interpretation of regression results

In this study a two-way fixed effects regression to analyse the relationship between digital acquisitions and the number of digital patents filed. In our short-term model, we found that the coefficient for the independent variable, digital acquisition, was statistically significant at the $p < .01$ level. Similarly, in the long-term model, we also found a statistically significant result at the $p < .01$ level.

Given that both models yielded results that are statistically significant at an alpha significance level below what was established for this study (5%), we cannot reject the null hypothesis. Thus, the evidence supports the hypothesis that "*There is a relationship between the acquisition of digital companies and digital patents for non-digital businesses*". Overall, the results from our regression of the short-term and long-term models provide strong support for the idea that digital acquisitions can play a role in the development of digital patents and by extension, a firm's digital capabilities.

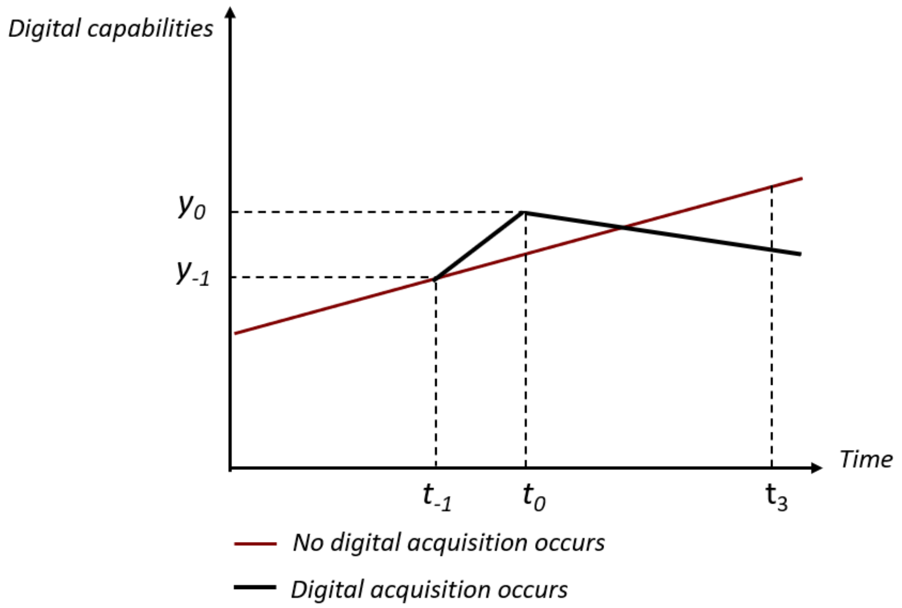

Figure 6. Generalised representation of regression results showing the effects of a digital acquisition on digital capabilities over time.

Interestingly, however, the regression coefficients for the independent variable showed the relationship to be positive in the short term and negative in the long term. By creating a linear piecewise function using the short and long term regression result coefficients from the independent variable, it is possible to create a generalized figure as illustrated in Figure 6. It shows that a firm that engages in a digital acquisition at year t_{-1} can be expected to have a significant surge in its digital capabilities ($y_{-1} \rightarrow y_0$) one year after the acquisition (t_0). On the other hand, however, we find that the firms that undergo the digital acquisition process sustain a significantly lower level of digital capabilities across the long term, in comparison to if it were to not undergo the same process, as can be seen at year t_3. Thus, the results further suggest that while digital acquisitions may offer a short-term boost to digital capabilities, they may also have negative long-term consequences.

As our regression results only provide discrete data points for what occurs during the years after an acquisition, it may therefore be unsuitable to assume that firms that engage in a digital acquisition will have a strictly linear decrease of their digital capabilities following year t_0 as depicted in Figure 6. Furthermore, given that our model specifications for the long run model account for the cumulative digital acquisitions conducted between the period t_{-3} to t_0, it remains to evaluate whether it is the number of acquisition deals completed during this period that causes this overall negative effect. Thus, further investigations into the timewise effect would be of great interest.

5.2. Evaluation of regression results

The adjusted R-squared value is a measure of the goodness of fit of a regression model, indicating the percentage of the variance in the dependent variable that is explained by the independent variables in a regression model. The adjusted R-squared value is a modified version of the R-squared that adjusts for the number of independent variables in the model. A higher adjusted R-squared value indicates a better fit of the model to the data.

In this study, the adjusted R-squared values for the short and long term models were 0.484 and 0.753 respectively, as seen in Table 3. These values are relatively high, indicating that the regression models provide a good fit to the data. This is particularly evident in the long term model, which has an adjusted R-squared value of 0.753, suggesting that the model explains a large proportion of the variance in the dependent variable.

It is worth noting that the adjusted R-squared value for the short term model is lower than that of the long term model, at 0.484. This may indicate that the short term model is less effective at explaining the variance in the dependent variable compared to the long term model. This difference may be due to the time frame of the study, as the long term model includes a longer time period, allowing for a more comprehensive examination of the relationship between the independent and dependent variables.

The values are similar to, albeit higher than, the adjusted R-squared presented in a study by Hanelt et al. (2021), of 0.38. This means that a higher degree of the variation shown in the dependent variable can be explained by our model.

Furthermore, the R-squared value measures the proportion of the variance in the dependent variable that is explained by the independent variables in a regression model. If the R-squared value is close to the adjusted R-squared value, it may indicate that the model is not overfitting the data. Overfitting occurs when a model fits the data too well, resulting in poor generalizability to new data. This can happen when the model includes too many independent variables, or when the independent variables are not appropriately chosen. The difference between the overall R-squared values, i.e. excluding R-squared (within), was low indicating that there was little to no overfitting in the models.

Moreover, an evaluation of the regression model assumptions should be considered. Our dataset showed no sign of multicollinearity, as all VIF values were below three with five being the limit for multicollinearity set in this study. As we logarithmized values in our data sample we also helped to ensure that there were a relatively low number of extreme outliers in the sample. The assumption of i.i.d could not easily be tested. To further support the results of this study such tests would need to be performed. As indicated in section 4.1, we found that the data for our dependent and independent variables were skewed. To this end, we also tested alternative specifications by taking the natural logarithm of each value +1 as a way of normalizing the data. The results from these tests however (untabulated) remained consistent with the overall result, showing a significant positive trend in the short term and a negative result in the long term.

5.3. Analysis of the results from the long- and short term.

Short term:

The results from our regression found that the short term effect on the digital capabilities of the acquiring firm to be positive.

The cause may be explained due to the acquired companies having a strong digital presence, with established digital products or services, advanced technology infrastructure, and skilled personnel. By acquiring a digital company, the firm can gain access to these digital assets and capabilities, allowing it to quickly and effectively increase its digital capabilities. This effect could be especially strong if the acquired digital capability is easily integrated into the acquired firm (Grant, 2021).

Moreover, the acquisition may allow the firm to diversify its digital offerings, expanding its reach and appeal to a wider range of customers. This could lead to increased revenue and market share, which in turn may provide the resources and motivation needed to further develop and enhance the digital capabilities of the acquiring firm.

What speaks against these results however, is that the short run model specification in this study looks at the effect of a digital acquisition one year after completion. This should be considered a relatively short time span for business to fully integrate into a new environment (Grant, 2021). Thus it may be unfitting to assume that the observed increase of digital capabilities relate to a successful integration. On the contrary, after acquiring a digital company, managers may feel pressured to quickly demonstrate the success of the acquisition to shareholders, especially if large amounts of resources have been invested (Grant, 2021). One way to do this is by extensively focusing on presenting an immediate improvement in the digital capabilities of the firm. This could involve rolling out new digital products or services, or integrating digital technologies into existing operations in order to enhance perceived output.

Long term:

The results of this study suggest that the long-term effect of digital acquisitions on digital capabilities is negative. This unexpected outcome could potentially be explained by the challenges that firms often face when integrating the operations of an acquired company.

As previously stated, one of the main reasons why firms choose to acquire other companies is to gain access to new talent and expertise (Grant, 2021). However, if the acquired employees do not feel satisfied with their new employer, for example, because of unsatisfactory data infrastructures, incompetent managers, or an unattractive pay package, their knowledge, skills and competencies will not be effectively utilised, ultimately making it more difficult to retain these skilful workers (Gressel et al., 2020). When key personnel depart, it can be difficult for the acquiring firm to retain the skills and knowledge that they brought to the table. This can lead to an overall decline in digital capabilities, over time.

Additionally, integrating the operations of two firms can be a complex and time-consuming process (Grant, 2021). According to Grant (2021), it may be difficult to align the cultures and systems of two fundamentally differing firms, and there may therefore be disruptions to the business, accounting for major internal inefficiencies, while the integration process is still taking place. The author shows that this may be particularly apparent when adopting a system that greatly differs from one's own, such as in the case of acquiring a firm that highly leverages the use of digital technologies into a traditionally non-digital business. This could lead to a decline in digital capabilities as resources are redirected towards integration efforts.

Even if the integration was done in an efficient and time-effective manner the acquiring firm will have to allocate significant resources towards the acquisition process (Grant, 2021). This could result in a diversion of resources away from initiatives that might have contributed to the development of digital capabilities. The shift in resources may also have hampered the development of existing business processes. This could lead to a decline in digital capabilities in the long run as the acquiring firm’s resources are stretched thin.

There is also reason to suggest that the negative effect may be explained by some level of strategic misalignment as brought up by Gressel et al. (2020). The acquiring firm and the acquired firm may have different strategic priorities and approaches to the use and development of digital capabilities. In this case, the acquisition may lead to a decline in digital capabilities as the acquired firm's capabilities are not utilized to their full extent or because they are not aligned with the acquiring firm's priorities. This can further be explained, according to Teece et al (1997), where the acquisition of a digital company from a non-digital acquirer such as an electric utility may only be justifiable if it builds upon or extends existing capabilities. This may be especially applicable to the digital frenzy where the fear of missing out may lead managers to make more reckless and uninformed decisions.

5.4. Results and prior studies

In section 2.2 we mentioned that a cause for acquisition can be to acquire specific databases, databases that are strategically important for the acquirer. If difficulties arise during the process of integrating the new databases it could also mean that the company has spent valuable resources, time, personnel and capital, on something that does not provide value for the company and thus contributes towards a reduction in the digital capabilities of the company.

Hanelt et al (2021) also studied the long term correlation of digital M&As on digital capabilities in the automotive industry and found a positive correlation. This is the opposite of what we found, and it is therefore of interest to discuss the potential discrepancies. There are a few factors that could explain the discrepancy, the most obvious one being the industry. While we analysed firms within the electric utility industry, Hanelt et al (2021) studied automotive companies. This coincides with studies showing that the success of M&As may potentially differ between industries (Rozen-Bakher, 2017).

Compared to the automotive industry, the electric utility industry has digitalized at a slower pace (Stewart et al., 2018). The perks of digitalisation might not be as large for electric utility companies that have completely different business models and where the speed of development and consequently the publishing of digital patents are slower than in other industries. In a slow-moving industry such as electric utilities (Stewart et al., 2018), it is possible that the positive effect of digital acquisitions takes longer to show. While an automaker, potentially, could use the newly acquired digital capabilities for the next car launch or software update, electric utility companies are more dependent on regulations and large investment decisions (Stewart et al., 2018).

Of the presented M&A types presented by Grant (2021): horizontal acquisition, geographical extension acquisitions, vertical acquisition, and diversifying acquisitions, we find none to be particularly prevalent regarding the process of adapting to a digital landscape and acquiring digital capabilities. The acquisition of digital firms can however still be said to correspond to the strategically motivated point of view, as the rationale relates to the procurement of resources and capabilities that are not easily transferable nor easily replicated, thereby requiring the acquisition of external resources.

6. Conclusion

In this chapter the knowledge contribution of the study is stated. Moreover, a conclusion of the analysis is presented and along with its implications on a broader perspective.

The purpose of the study was to provide a foundation for companies and investors to understand the potential implications of performing digital acquisitions on their digital capabilities. This was explored by analyzing the effects on digital capabilities of traditionally non-digital businesses that acquired the firms which highly leveraged digital technology. To this end, a two-way time and entity fixed regression model was adopted to investigate the relationship in the electric utility industry, during the years 2010-2021.

The results of this study provide evidence that there is a relationship between digital capabilities and digital acquisitions. Through the use of panel data and regression analysis, it was possible to indicate that the short term and long term effects of digital capabilities could be affected by the acquisition of digital firms.

Moreover, the study contributes to the existing research by providing a framework in which it is found that digital acquisitions have differing outcomes on a firm's digital capabilities in the short- and long term. The results indicate that firms that engage in digital acquisition deals display an increased digital capabilities in the short term, but sustain a decline in overall digital capabilities over the long term. The phenomenon may in part be explained by the difficulties in attempting to successfully integrate a highly digitalized company. However, further research is needed to fully understand the role that integration challenges play in this relationship.

Ultimately, we show that when trying to acquire digital capabilities, acquisitions may not be the best method for such purposes, which had previously been indicated to be true in prior research. Incidentally, we find evidence for managers to carefully address the potential benefits and drawbacks of digital acquisitions as there might be other more accessible, and better methods of obtaining the same desired target resources.

7. Discussion

The chapter puts the study into a wider perspective. This is done by presenting the limitations of the study and possible remedies for future studies in that regard. Future research opportunities are also presented based on our own findings and the state of the current research.

7.1. Limitations

With the restraints of our sources of data, we were unable to find sufficient data regarding the respective sizes of each digital acquisition. Thus we encourage future research to investigate this matter as it could prove to improve the accuracy of the model. It would be interesting to use the size of the digital acquisition both directly as a control variable and also to use the digital acquisition size relative to the size of the company as a control variable, thus taking firms' large size differences into account. It would also be of interest to include a measure of a firm’s research and development costs to the models as it might impact the success of the integration of the acquired company and subsequently the success of the integration of digital capabilities.

The collection of digital patents was a massively time-consuming process, having to manually look through over a thousands of patent descriptions and claims. Were the study to be conducted again a simpler approach toward identifying and listing digital patents would help immensely. Such a method would make it possible to extend the time frame of the study as well as enabling the incorporation of a greater number of firm being analysed. This would consequently result in better models and an understanding of the process of building digital capabilities through digital acquisition.

7.2. Future research

Further research is needed to determine whether the negative effects of digital acquisitions on digital capability are primarily due to the firms being in the process of integrating the acquired company. It would be interesting to explore whether these negative effects persist over the long term or if they are more pronounced during the mid-term, while the firms are still in the process of integrating the acquired company. This could provide valuable insights into the potential trajectory of the effects of digital acquisitions on digital capabilities over time.

Given a longer time span, it would also be of interest to investigate whether the negative effects of digital acquisitions on digital capabilities eventually dissipate and give way to positive effects in the even longer term. This could be due to the firms successfully overcoming the challenges of integration and reaping the benefits of the acquisition over time. Understanding the long-term dynamics of the effects of digital acquisitions on digital capabilities could help firms to make more informed decisions about whether and how to pursue such acquisitions as a way of increasing their digital capabilities.

In addition to the main results of the study, it would be valuable to further examine the outlier firms that showed an increase in digital capabilities in the short term but did not experience diminishing results in the long term. These firms may offer valuable insights into the factors that contribute to successful digital acquisitions and the development of digital capabilities over the long term. By investigating what separates these firms from the rest of the sample and identifying any contributing factors, future research may be able to shed light on the mechanisms that drive the relationship between digital acquisitions and digital capabilities over time. This could help improve strategies of firms looking to increase their digital capabilities through acquisitions, as well as inform policy efforts aimed at promoting the adoption of digital technologies

A qualitative study pertaining to the process of digital acquisition could add valuable insights to the research. From the initial reasoning, decision, and motives to follow through with a digital acquisition, to the steps taken to ensure a successful integration from the perspective of a manager would all be relevant in finding potential variables to explain the short- and long term effects observed in this study. The use of primary data in addition to secondary data sources would in this case also further help to provide a comprehensive and robust examination of the relationship between digital acquisitions and digital capabilities.

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9. Appendix

9.1. List of variables

Table 7. Description of the independent and dependent variables in the study.

Variable	Definition	Operationalisation	Calculation	Data Source
Digital Acquisition - Short term	"Acquisition of companies that intensely leverage digital technologies" – Digital acquisitions of a firm one year prior, t_{-1}, to the publishing of digital patents at t_0	Digital acquisitions were identified through manual evaluation of the acquisition information found on Thomson Reuters Eikons screener function. The columns Target Macro Industry and Deal Synopsis provided the most information for the evaluation.	Calculated as the number of digital acquisitions for year t_{-1}. Since data on digital patents was collected from 2010, the short term digital acquisitions variable spanned from 2009-2018.	Thomson Reuters Eikon
Digital Acquisition - Long term	"Acquisition of companies that intensely leverage digital technologies" – The cumulative amount of acquisitions that occurred between t_{-2} and t_0.	Digital acquisitions were identified through manual evaluation of the acquisition information found on Thomson Reuters Eikons screener function. The columns Target Macro Industry and Deal Synopsis provided the most information for the evaluation.	Calculated as the cumulative number of digital acquisitions that occurs between years t_{-2} to t_0. In the long term model, t_0 spanned from 2012 to 2019.	Thomson Reuters Eikon
Digital Patents - Short term	"Patents that highly leverage digital technology" - Digital patents of a firm at t_0 following the acquisition of a digital firm one year prior, t_{-1}	Digital patents were identified through manual evaluation of patent information retrieved from Espacenet. This process involved examining each patent to determine whether it met the definition of a digital patent, based on specific criteria. Once a patent was determined to be a digital patent, it was assigned to a particular year based on its filing date.	Calculated as the number of digital patents published in year t_0. The data used spanned from 2010-2019.	espacenet
Digital Patents - Long term	"Patents that highly leverage digital technology" - A firm's cumulative digital capabilities between t_0 and t_2.	Digital patents were identified through manual evaluation of patent information retrieved from Espacenet. This process involved examining each patent to determine whether it met the definition of a digital patent, based on specific criteria. Once a patent was determined to be a digital patent, it was assigned to a particular year based on its filing date.	Calculated as the cumulative number of digital patents published in years t_0-t_2. In the long term model, t0 spanned from 2012 to 2019.	espacenet

Table 8. Description of the control variables in the study.

Control variable	Description and calculation	Data Source
Size	Natural logarithm of revenue	Thomson Reuters Eikon
Leverage	Total debt divided by total assets - Measured in per cent	Thomson Reuters Eikon
Profit margin	Operating income divided by revenue - Measured in per cent	Thomson Reuters Eikon
Liquidity	Calculated as cash divided by total assets - Measured in per cent	Thomson Reuters Eikon
Capex	Capital expenditures - Measured in per cent	Thomson Reuters Eikon
Capital intensity	Natural logarithm of 1 + (Plant and equipment divided by average employees)	Thomson Reuters Eikon
Revenue growth	One-year growth of a firm's revenue in per cent.	Thomson Reuters Eikon

9.2. Keywords for patent search

Table 9. Shows the keywords used in the patent search together with an earlier study or report supporting the keyword.

Keyword	Reason/study
Cloud	Maroufkhani et al (2022); Gressel et al, 2020
Virtual Reality	Maroufkhani et al (2022)
VR	Maroufkhani et al (2022)
Digital Twin	Maroufkhani et al (2022)
IoT	Maroufkhani et al (2022); Gressel et al, 2020
Internet of things	Maroufkhani et al (2022); Gressel et al, 2020
AI	Maroufkhani et al (2022); Gressel et al, 2020
Artifical Intelligence	Maroufkhani et al (2022); Gressel et al, 2020
Visualization	Maroufkhani et al (2022); Gressel et al, 2020
CRM	Maroufkhani et al (2022)
Intelligent Agents	Maroufkhani et al (2022)
Middleware	Maroufkhani et al (2022)
Business Intelligence	Maroufkhani et al (2022); Gressel et al, 2020
Data Warehouse	Maroufkhani et al (2022)
Robotics	Maroufkhani et al (2022)
Sensors	Maroufkhani et al (2022)
RFID	Maroufkhani et al (2022)
3D Printing	Maroufkhani et al (2022)
Social Media	Maroufkhani et al (2022)
Minigrid	Maroufkhani et al (2022)
Microgrid	Maroufkhani et al (2022)
Virtual Power Plant	Maroufkhani et al (2022)
Smart	Maroufkhani et al (2022)
Mobile application	Maroufkhani et al (2022)
Wireless Network	Maroufkhani et al (2022)
5G Network	Maroufkhani et al (2022)
Digital	Maroufkhani et al (2022)
Augmented Reality	Maroufkhani et al (2022)
AR	Maroufkhani et al (2022)
Blockchain	Maroufkhani et al (2022)
DaaS	Gressel et al (2020)
AaaS	Gressel et al (2020)
Deep Learning	Gressel et al (2020)
Data Mining	Gressel et al (2020)
Augmented Intelligence	Gressel et al (2020)
Machine Learning	Gressel et al (2020)
SaaS	IEA (2017)
Autonomous	IEA (2017)

9.3. Search criteria for digital acquisitions.

Table 10. Shows the settings used in the search query of digital acquisitions in Thomson Reuters Eikon.

Screener function
Universe - Deals
Asset Class - M&A
Include - Company
Deal Participant Role - Acquiror, Acquiror Immediate Parent, Acquiror
Ultimate Parent, Acquiror Mid parent
Deal status - Completed (Conditional checked and not Unconditional)
Date effective - 01 Jan 2010 and 31 Dec 2019

Table 11. Shows the primary data that was imported for each acquisition.

Columns
SDC Deal No
Target Full Name
Target PermID
Target Macro Industry
Acquiror Full Name
Acquiror PermID
Deal Synopsis

9.4. Short and long term fixed effects regression results

```
Twoways effects Within Model

Call:
plm(formula = y0 ~ xt1 + c0 + c1 + c2 + c3 + c4 + c5 + c6, data = dataPanel_y0_xt1,
    effect = "twoways", model = "within", index = c("company",
        "year"))

Balanced Panel: n = 29, T = 11, N = 319

Residuals:
    Min.  1st Qu.   Median  3rd Qu.     Max.
-4.01292 -0.40043 -0.05391  0.23518 12.53363

Coefficients:
    Estimate Std. Error t-value Pr(>|t|)
xt1  0.61680    0.22616  2.7273 0.006801 **
c0  -0.75188    0.39654 -1.8961 0.059009 .
c1   3.52966    1.71694  2.0558 0.040758 *
c2   1.22355    1.04719  1.1684 0.243662
c3   1.94724    4.48068  0.4346 0.664208
c4   0.26531    1.35500  0.1958 0.844910
c5  -0.75371    0.39537 -1.9064 0.057657 .
c6   0.52540    0.20135  2.6094 0.009573 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    582.97
Residual Sum of Squares: 536.56
R-Squared:      0.07962
Adj. R-Squared: -0.076032
F-statistic: 2.94128 on 8 and 272 DF, p-value: 0.0036114
```

Figure 7. Two-way fixed effects regression output for the short term test results in R. The coefficient of digital acquisitions is 0.61680 and the respective p-value is 0.00680. The ANOVA p-value is 0.00361.

```
Twoways effects Within Model

Call:
plm(formula = y2 ~ x2 + c0 + c1 + c2 + c3 + c4 + c5 + c6, data = dataPanel_y2_x2,
    effect = "twoways", model = "within", index = c("company",
        "year"))

Balanced Panel: n = 29, T = 8, N = 232

Residuals:
     Min.   1st Qu.    Median   3rd Qu.      Max.
-8.232996 -0.996160 -0.041976  0.787348 11.753042

Coefficients:
   Estimate Std. Error t-value  Pr(>|t|)
x2 -0.90566    0.32863 -2.7558   0.00643 **
c0 -5.24663    1.08396 -4.8402 2.697e-06 ***
c1  8.28379    4.73019  1.7513   0.08153 .
c2  3.35130    2.43657  1.3754   0.17064
c3 11.72095   11.16607  1.0497   0.29521
c4  2.64020    3.98556  0.6624   0.50850
c5 -1.50418    0.97278 -1.5463   0.12372
c6  3.61352    1.70519  2.1191   0.03539 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    1549.6
Residual Sum of Squares: 1314.8
R-Squared:      0.15152
Adj. R-Squared: -0.042543
F-statistic: 4.1967 on 8 and 188 DF, p-value: 0.00012047
```

Figure 8. Two-way fixed effects regression output for the long term test results from R. The coefficient of digital acquisitions is -0.90566 and the respective p-value is 0.00643. The ANOVA p-value is 0.000121.

9.5. List of R-packages and functions

Table 12. Shows the R packages and functions used in statistical analysis and data handling.

Package	Function	Description/Purpose	Source
Tidyverse			Wickham et al (2019)
	as_tibble	Data formatting	Wickham et al (2019)
	mutate	Data formatting	Wickham et al (2019)
	read_excel	Data import	Wickham et al (2019)
plm			Croissant & Millo (2008)
	plm	Fixed-effects regression	Croissant & Millo (2008)
	pggls	Random-effects regression	Croissant & Millo (2008)
	phtest	Hausman test	Croissant & Millo (2008)
mctest			Imdadullah, Aslam & Altaf (2016)
	imcdiag	VIF test	Imdadullah, Aslam & Altaf (2016)