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The double-edged sword of Employee Downsizing: Examining the moderating roles of Digitalization and Industry Characteristics

Master Thesis

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Abstract

Digital technologies are transforming how firms capture and create value, forcing corporate strategists to reassess downsizing effectiveness in this new digital age. This thesis dives into the complex relationship between employee downsizing and firm performance in the context of digitalization and different industry characteristics. Grounded in the resource-based view, this thesis aims to better understand how this relationship evolves within the changing business environment. Results derived from automated content analysis and traditional financial data revealed that small-scale downsizing, depending on the industry, may be more disruptive than prior literature suggested. Furthermore, the findings did not significantly establish a decisive conclusion on the role of digitalization within the downsizing context, underscoring the complexity that surrounds employee downsizing. This thesis contributes to the existing body of knowledge on downsizing in literature and provides managers with valuable practical considerations when engaging in employee downsizing practices. It emphasises the need for careful assessment of firm and industry-specific factors.

Moreover, it leaves an interesting avenue for future research on how downsizing practices could leverage digitalization to reduce the negative impacts on firm performance. While literature suggests that digitalization can migrate negative impacts of downsizing, findings indicate that those capabilities are hard to leverage. Future research should aim to identify under which conditions digitalization can have a positive influence on the downsizing outcomes.

Keywords: Employee downsizing – Digitalization – Firm performance – Industry characteristics – Resource-based view

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Introduction

Over the past few decades, employee downsizing has become a well-known practice within the organisational context and is frequently viewed as vital in the increasingly competitive global marketplace. Downsizing is said to be “one of the most far-reaching and significant management issues of the current era” (Datta & Basuil, 2015, p. 198). What originated within US companies, with an average of 4,000 employees being downsized every business day between 2000 and 2007, has become a global managerial practice (Datta & Basuil, 2015). Within the first month of 2024, more than 776 companies have announced mass layoffs, companies such as Continental AG (7150 No. of employees to be laid off), Cisco Systems (4000 No. of employees to be laid off), and UPS (12,000 No. of employees to be laid off) have announced that they are reducing their global workforce starting as of February 24’(Intellizence, 2024).

With future costs being more predictable than future revenues and the constantly changing business environment, companies often engage in downsizing to halt and reverse expected performance declines (Datta & Basuil, 2015). As the world around us changes, so do managerial practices and their outcomes. The increased adoption of technology in our everyday lives has changed business practices and calls for new understandings of corporate strategies and how businesses behave and perform within this evolving digital world (Menz et al., 2021).

For more than two decades, technological innovations have been the fundamental driver of economic growth (Brynjolfsson & McAfee, 2017). The digital world is a constantly changing factor, forcing organisations to closely pay attention to the development of new technologies to adapt their strategies and business models to the new market needs (Caputo et al., 2021). Digital technologies are changing the ‘rules of the game’ in many industry sectors as to where and how to compete, what business model to choose, and how to balance creating versus capturing value (Birkinshaw, 2017). In 2019, the COVID-19 pandemic resulted in unforeseen global contract restrictions, forcing companies and industries to respond and adapt to the rapidly changing environment by accelerating their digital transformation efforts (Barker et al., 2022). The rapid acceleration changed traditional ‘offline’ business models and created a high degree of environmental uncertainty, fostering firm decline and turbulence. The changing business environment also impacted business practices and knowledge regarding corporate turnaround, which refers to a recovery strategy for a firm’s financial performance (Barker et al., 2022; Schendel et al., 1976).

One of the strategic actions considered as a critical part of the turnaround strategy to strengthen a firm's ability to remain a viable business entity is employee downsizing (Norman et al., 2013). Employee downsizing is described as: " the planned elimination of positions or jobs" (Cascio, 1993, p. 96), and is seen as a quick way to enhance firm performance and generate financial benefits by reducing operating costs, streamlining operations and eliminating unnecessary management levels (Cascio, 1993; Datta et al., 2010; De Meuse et al., 2004; Gandolfi, 2010). Prior research also underscores possible negative outcomes for organisations such as reduced profits, decreased employee morale and satisfaction (De Meuse et al., 2004), increased work-related stress (De Vries & Balazs, 1997) and a negative effect on corporate reputation (Zyglidopoulos, 2005).

These mixed findings show that the relationship between employee downsizing and firm performance has not yet reached a consensus. Some argue that employee downsizing has a positive effect, while others argue that employee downsizing has a negative effect on firm performance. Moreover, the effectiveness of employee downsizing on firm performance in different contexts, different industries and over a different time span lacks consensus. Questions regarding "What constitutes a good downsizing?", "Which circumstances result in value being created rather than being destroyed?" and "How does employee downsizing influence long-term firm performance?" remain unanswered (Datta & Basuil, 2015, p. 216). Understanding the impact of employee downsizing under different influences is crucial for making informed strategic decisions to ensure long-term success (Barker et al., 2022; De Meuse & Dai, 2013; Guthrie & Datta, 2008).

Building upon the double-edged sword of employee downsizing, this thesis aims to explore how the effect of employee downsizing on firm performance evolves within the changing digital landscape. The COVID-19 pandemic accelerated the digital transformation within organisations, adding a new layer of complexity to corporate strategies (Barker et al., 2022). Volberda et al. (2021) emphasised that digital transformation is changing a lot of traditional understandings regarding strategy. While digitalization is often associated with efficiency gains, the flipside of the coin is that it also adds complexity and agility to strategic foresight, planning and control. The speed, scale, scope, and high level of ambiguity in the changing digital ecosystem make traditional assumptions about strategy irrelevant, highlighting the need for more research on how employee downsizing evolves within this complex environment (Barker et al., 2022; Volberda et al., 2021).

This thesis aims to add an extra layer to the discussion by researching how digitalization and industry characteristics moderate the effect that employee downsizing has on firm performance. Based on prior literature, the following research question has been formulated to study the effect of the magnitude of employee downsizing on the firm performance with the moderating effect of digitalization and industry characteristics:

"Does the magnitude of employee downsizing influence firm performance, and what is the role of digitalization and industry characteristics on this relationship?"

To answer the research question, the following sub-questions were derived from the main topics: 'Employee downsizing', 'Digitalization', 'Firm performance', and 'Industry characteristics':

- How does employee downsizing impact firm performance?
- How does digitalization influence the relationship between employee downsizing and firm performance?
- How do industry characteristics influence the relationship between employee downsizing and firm performance?

Figure 1 shows the conceptual model, which integrates all the hypotheses derived from the research question

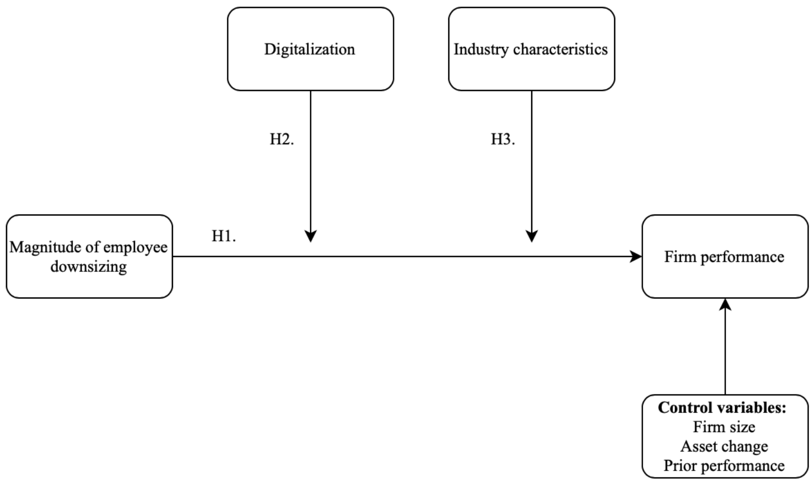

Figure 1: Conceptual model

Theoretical background

Employee downsizing, the planned reduction of personnel within organisations, has become increasingly relevant in response to the shifting global and technological landscape (Cascio, 1993; Menz et al., 2021). This chapter will delve into the main variables of this research with the help of a literature review. First, the concept of employee downsizing will be explained, followed by firm performance and the relationship between both variables. Finally, the moderating relationship of digitalization on employee downsizing and firm performance will be examined followed by how industry characteristics could influence this relationship.

Understanding sources of sustained competitive advantage for firms has been a major area of research in the field of strategic management. Over the past decades, the resources-based view has become a well-established theory to explain differences in firm performance (Karim et al., 2022) The resource-based view (RBV) highlights the importance of a firm's resources and ownership in creating and sustaining a long-term competitive advantage, as these resources directly influence long-term firm performance (Barney, 1991; Chen et al., 2021). According to the resource-based view, a firm's post-downsizing effectiveness is contingent on the presence and utilisation of resources that can be leveraged to the firm advantage (Norman et al., 2013). These resources can be classified into three categories: physical capital resources, human capital resources, and organisational capital resources (Barney, 1991). With employee downsizing possibly detreating existing human capital resources, this thesis adopts the resource-based view as a theoretical lens to analyse how employee downsizing impacts firm performance (Kim et al., 2020).

Employee downsizing

Downsizing can involve reductions in various combinations of physical, human or capital resources, this research focuses on employee downsizing, which concerns personnel reductions in the organisational context (Datta et al., 2010). Employee downsizing is traditionally described as "the planned elimination of positions or jobs" (Cascio, 1993). More recent studies describe employee downsizing as "*a planned set of organisational policies and practices aimed at workforce reduction with the goal of improving firm performance*" (Datta et al., 2010, p. 283). And "*changes in the absolute number of jobs, changes in job occupancy due to redefinitions of positions and responsibilities, and disruptions of organisational relationship networks*" (Brauer & Laamanen, 2014, p. 1312).

Over the last couple of years, employee downsizing has gained more and more attention from organisations and researchers due to changes in the global macro and business environment. Changes in globalisation and increased foreign competition made firms constantly look for ways to reduce costs and improve their competitive advantages. As a result, firms started offshoring and outsourcing their operations to countries where value-added activities can be performed at much lower costs, leading to increased levels of downsizing in the firm's home countries (Datta & Basuil, 2015). Another critical factor underlying the increased attention on downsizing pertains to the rapidity of technological and societal change. In the past, organisations were valued on stability and predictability, now organisations must be flexible, agile, versatile, and adaptable, altering the way that management views workforce stability (De Meuse et al., 2011). Downsizing decisions are therefore influenced by both external environmental and internal organisational context factors. Downsizing outcomes, both organisational and individual, are affected by factors related to the decision and implementation process (Datta et al., 2010).

In today's knowledge-based economy, jobs tend to be more complex and varied, requiring more skills and more profound knowledge sets, making an organisation's human capital and intellectual capital of critical value (De Meuse et al., 2011; Guthrie & Datta, 2008). Central to the resource-based view is the importance of human, social and intellectual capital as key resources for long-term viability and competitive advantage (Norman et al., 2013). Within the organisational context, employees not only account for their knowledge and skills but also contribute to the firm's tacit knowledge and capabilities by collaborating and integrating their skills. As a result, both human and social capital rely on the commitment and loyalty of employees in creating competitive advantages (Guthrie & Datta, 2008; Norman et al., 2013). The basic notion surrounding employee downsizing is that by decreasing the firm's costs through the reduction of personnel, profits can be increased, improving the firm's chances of long-term survival (Cascio et al., 2021; Schenkel & Teigland, 2017). While employee downsizing immediately leads to labour cost savings, it also critically affects employee commitment and loyalty, disrupting existing relationships and damaging human capital, which could negatively impact the firm's competitiveness and performance (Aalbers, 2020; Guthrie & Datta, 2008; Norman et al., 2013).

Because of this damage to human capital, employee downsizing is often seen as a breach of the psychological contract between employees and their employers. The psychological contract theory generally refers to the exchange relationship wherein two parties trade things of value, mainly between the employee and the organisation, based on trust and informal codes

(Datta & Basuil, 2015; Hansen et al., 2015). If one of the parties perceives that the other has violated this exchange, negative consequences can occur. Employees who experience downsizing therefore may adjust their organisational contributions and neglect to perform activities that would benefit organisational goals. In addition, employees who undergo downsizing are reported to experience more work-related stress, less work satisfaction, decreased loyalty and fewer learning and development opportunities, resulting in lower levels of engagement (De Meuse et al., 2011; Dlouhy & Casper, 2021). These negative implications reduce the value derived from the firm's human capital, which also negatively impacts the firm's competitive advantages and weakens the long-term firm performance (Norman et al., 2013). A recent meta-study by Datta and Basuil (2015) suggested that the magnitude of these negative implications probably differs within different cultural contexts and industry characteristics. The nature of for example psychological contracts in Japan is much more embedded in their culture than for US-based firms. Given the cultural Japanese context of the lifetime employment policy, employees perceive downsizing much differently than US-based employees. Thus, probably altering the negative implications due to the breach of psychological contract within different cultural contexts.

The negative effects of downsizing were reported to be more pronounced in faster-growing industries. During times of market expansion, downsizing was argued to be more harmful to employee morale and commitment, therefore reducing organisational effectiveness (Datta & Basuil, 2015; Guthrie & Datta, 2008). Negative effects attributed to the employee perceptions of downsizing seemed to be reduced in times of downturn (Kao & Chen, 2020). Jung and Lee (2021) explored how financialisation contributed to the changing environment of employee relations. They found that the push for shareholder value maximisation influenced downsizing decisions, even when labour unions resisted, thereby breaching established relationships. Many of the problems of downsizing are related to the fact that downsizing deleterious impacts the relationship between employees and the firms. When downsizing is carried out with haste and without careful evaluation to the circumstances in an effort to rapidly reduce payroll costs, downsizing can become a source of problems with firms often removing the organizational 'muscles' rather than the 'fat' (Datta & Basuil, 2015).

Overall, the literature perceives employee downsizing as an instrument to reduce costs and improve a company's competitive advantage (Datta & Basuil, 2015). Over the last couple of years, rapid technological and societal changes in the business environment have led to increased levels of downsizing (De Meuse et al., 2011). While employee downsizing immediately reduces labour costs, it can also lead to long-term negative effects (Guthrie &

Datta, 2008; Norman et al., 2013). Breaches in psychological contracts between employees and organisations result in less work satisfaction, increased stress levels, and less employee commitment. These breaches in psychological contracts due to downsizing could eventually reduce the value derived from human capital, negatively influencing the firm's long-term performance. The magnitude and impact of the negative implications vary for different industry characteristics and contexts. Therefore, while employee downsizing is generally seen as a 'quick fix' to improve firm performance, the negative consequences are often overseen. The impact of downsizing on human and social capital in different cultural contexts and market conditions needs to be assessed carefully to ensure the long-term benefits of downsizing (Datta & Basuil, 2015; Guthrie & Datta, 2008).

Employee downsizing and firm financial performance

While Employee downsizing is generally seen as an organisational response to situations involving a decline in demand due to changes in industry or economic conditions, it is important to recognise that not all downsizing happens as a response to poor organisational performance. Employee downsizing can be divided into two broad dimensions: reactive and proactive downsizing. Reactive downsizing takes place after performance has declined and focuses on short-term needs, mainly aimed at cost containment and is considered a defensive response in times of crisis. The second dimension, proactive downsizing, takes place when performance has not yet declined, aimed to support the long-term organisation strategy in anticipation of potential competitive challenges. Proactive downsizing is often linked to organisational restructuring, changes in internal processes and shifts toward flatter organisational structures. This research aims to understand how employee downsizing influences firm performance, regardless of the type of downsizing (Datta & Basuil, 2015; Kao & Chen, 2020; Love & Nohria, 2005; Parker et al., 1997).

Previous studies have reported that the type of downsizing influences the effect on accounting outcomes. Proactive downsizing, related to efficiency improvements and refocusing, contributed to improved post-downsizing profitability. Reactive downsizing, driven by a decline in demand, resulted in negative accounting returns (Datta & Basuil, 2015). Cependes et al. (2019) added that when firms engage in proactive downsizing, the psychological contract between employees and the firm could be broken. With proactive downsizing happening when performance has not yet declined, employees could feel like they have been betrayed. Due to the lack of understanding by employees, commitment and morale could be destroyed, undermining both productivity and morale and thus negatively influencing firm performance.

Both types of downsizing, whether driven by external pressures or strategic considerations, represent a set of activities that are focused on improving the efficiency of the organisation (Cameron, 1994; Kao & Chen, 2020).

Recent evidence on the direct relationship between employee downsizing and firm financial performance is mixed. While some studies suggest a positive relationship, indicating improved financial performance post-downsizing, others found that employee downsizing often does not lead to increased financial performance (Cascio et al., 2021; Céspedes-Lorente et al., 2019). Most research related to the impact on the firm's financial performance primarily focuses on the following accounting measures: return on assets (ROA), return on equity (ROE) and return on sales (ROS) (Datta & Basuil, 2015). De Meuse and Dai (2013) found that downsizing companies were initially outperformed by non-downsizing companies on return on assets, profit margin and revenue growth, which was in line with earlier research on this subject. The financial difference diminished over time, confirming the findings of prior research. Although being outperformed by non-downsizing firms during the research period, the study of De Meuse & Dai (2013) interestingly found evidence of positive organizational financial outcomes post-downsizing. Cascio et al. (2021) also confirmed this by finding positive financial outcomes for post-downsizing firms, Cascio added that a combination of both asset and employee downsizing could create even bigger financial gains. Brauer and Laamanen (2014) highlighted that the magnitude of downsizing plays an important role in the post-downsizing performance of European firms. Based on prior research Brauer and Laamanen made a distinction between three different magnitudes of downsizing. Small-scale downsizing (5-10 percent), medium-scale downsizing (10-20 percent) and large-scale downsizing (>20 percent), finding support for a U-shaped relationship between the magnitude of downsizing and firm performance (Brauer & Laamanen, 2014).

A recent study that looked into the non-linear relationship of the employee downsizing magnitude within Dutch organisations also found support for a U-shape relationship (Van Boven & Aalbers, 2021). In their meta-analysis, Datta and Basuil (2015) examined 55 studies, to assess whether downsizing did improve organisational performance. They found that prior research was equivocal, with little agreement among researchers on the efficacy of downsizing in creating organisational value. Both US and non-US-based studies were analysed finding that the inconsistent and equivocal findings also manifested themselves within the different contexts. While research on the relationship between the magnitude of employee downsizing and firm performance lacks consensus, most research implies a negative relationship. The permanent damage to psychological contracts and critical loss of human and social capital, essential for a sustained competitive advantage, negatively impact the firm performance. Therefore, the following hypothesis has been proposed:

H1. The magnitude of employee downsizing is negatively related to firm performance.

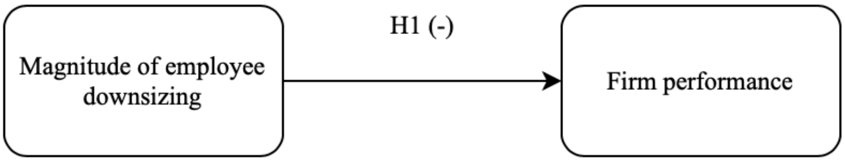

Figure 2. Hypothesis 1

Digitalization

Digitalization is transforming how firms create, deliver and capture value. Digitalization is often confused with digitization and can be interpreted from many perspectives. According to Autio et al. (2021), “Digitalization is the organisation and utilisation of algorithms and digital data structures for the performance of control, communication and execution of tasks, largely operationalised through networked computer hardware and layers of firmware, middleware, and software, connected through a set of standardised interfaces such as application programming interfaces” (Autio et al., 2021, p. 6). Whereas digitisation purely concerns the process of transforming streams of analogue data into a digital format, for example shifting from using handwritten notes to using words (Autio et al., 2021; Caputo et al., 2021).

New trends in the business environment and rapid technological advances provide us with new capabilities, changing how we live, work, and relate with each other. This so-called fourth industrial revolution driven by technological advancements like artificial intelligence, robotics and the internet of things, is unique in the velocity, breadth and impact at which these changes shape our lives and understandings (Schwab, 2017). The emergence of this new ‘digital age’ is fundamentally challenging our understanding of the nature and functioning of multi-business firms in terms of corporate strategies and performance (Menz et al., 2021). This wave of digitalization and widespread adoption of technology allows firms to optimise existing business processes, modify the firm’s organisation design and adjust value-creating and capturing activities within the entire value chain (Barker et al., 2022; Volberda et al., 2021). With new challenges due to the Covid-19 pandemic restrictions, organisations were forced to accelerate their digital transformation efforts to keep competing, forever changing the ‘rules of the game' in many industries, challenging strategising in several ways (Barker et al., 2022; Hanelt et al., 2021; Volberda et al., 2021). It is clear that this so-called fourth industrial revolution is changing our everyday lives, "what is less clear is how these digital technologies affect corporate strategy and the economic, sociological and behavioural foundations of the firms" (Menz et al., 2021, p. 1697).

Digitalization and firm performance

In the digital age, performance depends on a firm's ability to adapt to changes in its business environment. Traditional fixed resources are becoming less important, which makes firms rather possess the ability to continuously reshape their resources, relying more on dynamic capabilities to maintain their growth and gain competitive advantage. Digitalization plays a crucial role in creating a competitive advantage by enabling firms to quickly gather market data at low costs in multiple dimensions to perceive market change and identify opportunities and threats before competitors. By leveraging ICT, businesses can reduce input costs, streamline operations and enhance greater agility. This improved agility plays a crucial role in reducing the impact of possible uncertainty on business operations, allowing organisations to maintain their competitive advantages in the changing business environments and thereby increasing their overall performance (Seo et al., 2012; Verhoef et al., 2021; Zeng et al., 2022). Digitalization is not just something that can be leveraged overnight. For organisations to fully benefit from digitalization, achieving digital maturity through a clear strategy for implementing and exploiting digital technologies is crucial to ensure future business success (Bharadwaj et al., 2013; Hess et al., 2016; Kane et al., 2017; Sebastian et al., 2020).

The widespread adoption of digital technology also leads to changes in how firms divide their workforce. Simple, repetitive tasks are slowly being replaced by automation, which is quickly copied by other firms, contributing to enhanced efficiency across the entire economy. Complex tasks that cannot be fully automated increase the demand for highly skilled workers who can fulfil these tasks. The increased demand down the entire economy results in higher labour costs, more consulting expenses and increased costs of digital ability training for managers and employees. Therefore the more enabling technologies are used by firms, the higher the management expenses, impacting firm performance (Guo et al., 2023; Seo et al., 2012). Contrarily, digitalization may decrease the costs of transacting and coordinating, thanks to automation and greater transparency, resulting in fewer human errors (Menz et al., 2021). A consensus on the effect of digitalization on firm performance has not yet been met. Some researchers argue that digitalization can significantly improve firm performance, (Zeng et al., 2022) while others found a negative impact on firm performance (Guo et al., 2023).

Digitalization and employee downsizing

Few studies have analysed the relationship between digitalization and employee downsizing. In the organisational context, employees are not only contributing by delivering individual skills and knowledge but also through a collaborating group that integrates their separate skills toward creating valuable firm resources (Guthrie & Datta, 2008). Research on employee downsizing found that the negative impact of workforce reduction is often overseen, the damage to human capital results in the loss of valuable employee knowledge, skills and organisational learning capacity. Not only the human capital is damaged, but the removal of individuals also alters the firm's social structure and hence its social capital, deteriorating workforce productivity and therefore worsening the firm's economic performance (Céspedes-Lorente et al., 2019).

The so-called holy grail of business success is to earn a sustainable competitive advantage, a situation where a firm performs better than its competitors and where this advantage is not quickly eroded (Knudsen et al., 2021). In today's world, digitalization is seen as a key instrument for organisations when striving for competitive advantage (Céspedes-Lorente et al., 2019). While the importance of a firm's digital technology as a corporate-level resource increases it will probably make human capital decisive as a corporate competitive advantage (Menz et al., 2021). The evolving business literature emphasises that the usage of digital technologies can become a factor that complements human capital and contributes to social and organisational capital (Céspedes-Lorente et al., 2019; Schneider, 2018). Digitalization allows employees to leverage big data for better decision-making and facilitates knowledge sharing through collaboration platforms. Additionally, machine learning systems are becoming superior at many tasks that were previously done by the most intelligent humans, enabling organizations to rely less on employees when performing certain activities (Autio et al., 2021; Brynjolfsson & McAfee, 2017; Menz et al., 2021). Digitalization, as a valuable resource, can therefore enhance organisational learning by facilitating information sharing and collaboration among employees. Furthermore, digitalization extends organisational memory, highly advanced computerized systems make it possible to capture tacit knowledge, potentially filling the knowledge gap that downsizing leaves behind. Over time, firm-level accumulation of different kinds of knowledge could form a database that facilitates future knowledge and enhances organisational learning, contributing to improved firms' financial performance (Céspedes-Lorente et al., 2019; Kuusisto, 2017).

The evidence within this section suggests that digitalization could positively moderate the effects of employee downsizing on firm performance, arguing that potential negative effects of workforce reduction can be mitigated by the integration of digital technologies (Céspedes-Lorente et al., 2019). Based on this perspective, the following hypothesis has been formulated:

H2: Digitalization positively moderates the effects of employee downsizing on firm performance

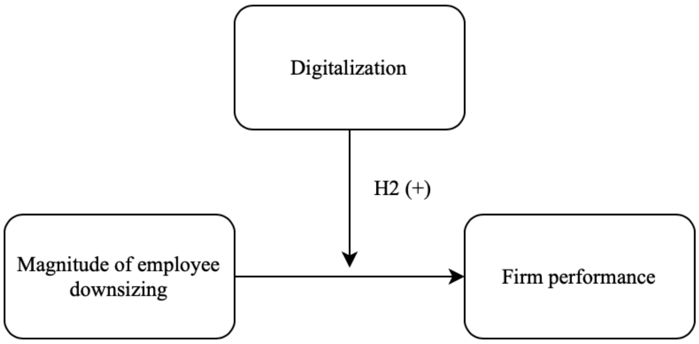

Figure 3. Hypothesis 2

Industry characteristics

Research found that industry characteristics influence the effects of employee downsizing on firm performance (Guthrie & Datta, 2008). While downsizing may result in immediate labour cost savings, it could also seriously deteriorate employee commitment and loyalty, negatively affecting the firm's competitiveness and performance. With the RBV as a theoretical lens, researchers argued that different industry characteristics modify the performance consequences of the loss of human capital, social capital and decrease of commitment and loyalty among the remaining employees. With jobs differing in terms of complexity, skills and knowledge sets across different industries come different disturbing effects that employee downsizing has on human and social capital. With the process-dependent nature of workforce relations within technologically intensive industries, any disruptions triggered by downsizing will likely have a major impact on firm outcomes (Guthrie & Datta, 2008). Cascio added that organisations with the greatest risk of negative effects are those that operate in rapidly evolving industries in which survival depends on a firm's ability to innovate constantly, such as biotechnology pharmaceuticals and software (Cascio, 2002). Within R&D-

intensive industries, downsizing seemed to be more harmful due to the loss of critical human and social capital in combination with lower commitment and greater rigidity under the surviving employees. In addition to these findings, the growth rate of the industries seems to also influence the relationship between employee downsizing and firm performance, the negative effects of downsizing were more pronounced in faster-growing industries. Moreover, downsizing was deemed more acceptable by employees in declining or mature industries, probably because employees seemed to anticipate a possible downsizing (Guthrie & Datta, 2008; Kao & Chen, 2020). How this relationship develops with the increasing adoption of digitalization across all industries remains unknown. Building upon earlier research on the relationship between industry conditions and the effect of downsizing on firm performance the following hypothesis has been formulated:

H3: Industry characteristics negatively moderate the relationship between employee downsizing and firm performance

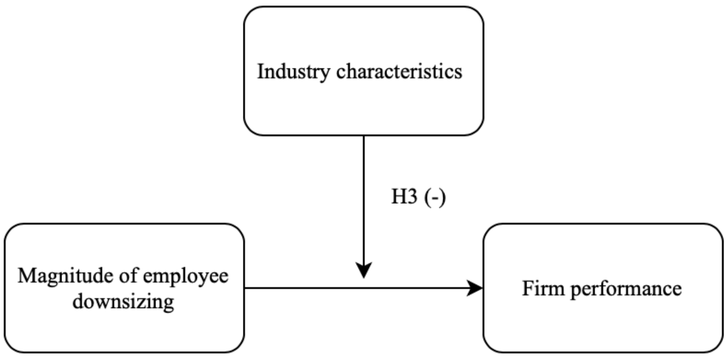

Figure 4. Hypothesis 3

Methodology

Empirical setting and method

To test the hypothesized relationships, a quantitative study in the context of employee downsizing was carried out. The sample consists of S&P 500 and STOXX Europe 600 index firms that performed at least 5% employee downsizing between 2010-2020. This period is chosen to ensure all data is present and to limit the chances of missing data. The S&P 500 and STOXX Europe 600 represent a broad mix of industries, allowing for a broader generalizability of the findings. LSEG data & analytics is used to retrieve both financial data and employee counts. The initial data sample consisted of 1106 firms listed in either of the indexes within the period. After manually checking for missing data, anomalies and out-of-ordinary data, the final sample comprised a total of 1095 observations derived from 571 unique firms that downsized at least 5% of their employees in the given time period. To analyse the data, a multiple regression analysis has been conducted to estimate the relationship between employee downsizing and firm performance in relation to the different moderating factors.

The annual reports used for the assessment of digitalization were hand-collected from public web sources for the relevant period. Once all the annual reports were collected, they were manually converted to .txt format to facilitate further analysis. Following the collection and conversion, the annual reports were analysed using a Python script called TextExtractor (Van Boven & Aalbers, 2018). TextExtractor employs regular expressions, enabling users to automatically search for specific words, word combinations and sentences within text documents (Van Boven & Aalbers, 2018). This automated approach allows users to quickly analyse large volumes of documents, making it a lot less time-intensive compared to traditional content analysis methods. The TextExtractor looks for the different predefined regular expressions through the annual reports and reports the findings, indicating which expressions are present in each annual report. This output is then utilized to construct the variable ‘digitalization’, quantifying the extent of digitalization within the sample firms.

Measurement of variables

Independent variable

Employee downsizing, the independent variable in the research, is commonly defined as "*changes in the absolute number of jobs*" (Brauer & Laamanen, 2014, p. 1312). Consistent with previous research, employee downsizing is measured as the percentage change in the number of employees compared to the year prior:

$$Employee\ downsizing = \frac{N\ of\ employees\ (t+1) - N\ of\ employees\ (t+0)}{N\ of\ employees\ (t+0)} * 100$$

Prior research on employee downsizing typically chooses a specific cut-off point in workforce reduction to represent downsizing. The most common cut-off point is 5 percent. In the event of a 5 percent downsizing, it likely indicates an intentional reduction in employees, a feature of downsizing. This research therefore follows earlier research and uses 5 percent as a specific cut-off point to represent downsizing (Guthrie & Datta, 2008).

To add extra depth and robustness to the findings, this study also tested for different magnitudes of employee downsizing. In line with the methodology of Brauer and Laamanen (2014), employee downsizing was divided into three different magnitude categories:

- 1: Small-scale downsizing (5-10%)
- 2: Medium-scale downsizing (10-20%)
- 3: Large-scale downsizing (>20%)

Dependent variable

Firm performance, the dependent variable, is measured as *return on assets (ROA).* Return on assets is the most widely used firm performance variable in research on employee downsizing and strategic management. The return on assets is measured as operating income (before depreciation, interest, and taxes) divided by total assets. ROA accounts for an indicator of the extent to which firms' assets generate profit (Aalbers et al., 2014; Cascio, 1998; Guthrie & Datta, 2008). The return on assets is measured as:

$$Return\ on\ assets = \frac{[1/3(\ ROA_{t+1} + ROA_{t+2} + ROA_{t+3}) -\ ROA_{t-1}}{ROA_{t-1}}$$

Following the path of prior research, this research assessed the effect of workforce downsizing by using the change in ROA in a three-year post-downsizing period (t+1 to t+3) relative to the year prior to downsizing (t-1). By using multiple years of performance following the downsizing, a more robust test of the influence of employee downsizing on performance can be conducted, which is consistent with previous research (Brauer & Laamanen, 2014; Guthrie & Datta, 2008). Return on asset was winsorized at the 1st and 99th percentiles of the empirical distribution to reduce the effect of outliers[1]

Moderating variables

Digitalization, measuring the degree of a firm's digitalization can be difficult, costly and time-consuming. This research, therefore, uses a text mining method to extract predefined keywords from annual reports that relate to digitalization. Annual reports, which reflect the current firm strategy and situation, are considered a good representation of digitalization within a firm (Zeng et al., 2022). The annual reports were manually retrieved for all the sample companies over the ten years and analysed with a phyton script called TextExtractor (Van Boven & Aalbers, 2018). This script allows users to look up certain words, word combinations and sentences in batches of text documents.

To operationalize the variable digitalization, a dictionary with keywords and word combinations related to digitalization was constructed. Keywords were gathered from existing literature, hype cycles from Gartner and Deloitte and papers that performed similar text analysis (Wang & Bai, 2024; Zeng et al., 2022). To increase the validity of the dictionary, input from a researcher, a PWC consultant and an enterprise architect was sought to ensure that the dictionary accurately captures the concept of digitalization as intended. To make sure that the regular expressions were extracting the correct information, a test sample was run before running the whole text analysis. The list of regular expressions can be found in Appendix A.

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[1] During the initial analysis, some questioning outlying values for Return on assets were present. Outliers can provide valuable insights, so the decision was made not to delete them but to winorize them to suppress the weight that could possibly be the result of external factors not related to employee downsizing while partly retaining the possible valuable information.

Before extracting, the weight in which each expression reflects digitalization was determined based on the Gartner and Deloitte hype cycles of the corresponding year. For example, the presence of "Blockchain technology" in 2010 has a heavier weight of reflecting digitalization than in 2020 after "Blockchain technology" became a more widely used concept. To account for the rapid technological advances over time, a three-point marking scheme was developed to rank every expression of digitalization over the 10-year period.

- 1: Low digitalization
- 2: Medium digitalization
- 3: High digitalization

The ranking scheme of the expressions can be found in Appendix B. After running the text analysis, the degree of digitalization for each firm was manually calculated for the corresponding year based on the marking scheme resulting in the following categories:

- 0: No digitalization (zero hits with text analysis)
- 1: Low digitalization
- 2: Medium digitalization
- 3: High digitalization

Industry characteristics, the second moderator is operationalized as industry fixed effects[2] to account for industry differences. The industries were operationalized based on the ICB classification to account for the international character of the sample and categorized into six dummy variables: Technology and Telecom (11%), Financial and Real Estate (21%), Consumer and Discretionary (19%), Industrials and Materials (28%), Healthcare (6%) and Energy and Utilities (14%).

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[2] When calculating for specific industry characteristics there were over 350 missing values making it an unreliable operationalization. To account for different industry effects the choice was made to add dummy variables for the industries to capture the fixed effects. Fixed effects can be interpreted as unobserved characteristics of industries that are constant over time and are industry specific (Wooldridge, 2010).

Control variables

Prior performance, the first control variable, is measured as the mean return of assets for the three years preceding the employee downsizing. Controlling for prior performance allows to assess the impact of employee downsizing on firm performance over and above previous firm performance (Brauer & Laamanen, 2014; van Boven & Aalbers, 2021).

Firm size, the second control variable, is measured as the logarithm of total assets. Prior research has argued and found that firms that grow beyond their optimal size tend to benefit more from employee downsizing (Brauer & Laamanen, 2014).

Furthermore, this research also controls for *Asset change*. Controlling for asset change allows for the isolation of the effect of workforce downsizing over the change in the physical scope of firm operations. Asset change was measured as the percentage of change in firms' total assets in the year the workforce reduction took place compared to the previous year (Brauer & Laamanen, 2014; Guthrie & Datta, 2008). Table 1 provides an overview and explanation for all variables.

Table 1. Variable explanation

Variable	Code	Variable type	Measurement	Database
Firm performance	ROA_Winsorized	DV	Operating income divided by total assets	LSEG
Employee downsizing	Downsizing	IV	Percentage change in the number of employees compared to the year prior:	LSEG
Digitalization	Digital	Moderator	Ranked with help of text extraction	Open source
Industry characteristics	In_Financial_RealEstate e.g.	Moderator	Dummy variables that	LSEG

			equal 1 if industry 0 otherwise	
Prior performance	Prior_performance	Control	The mean return of assets for the three years preceding the employee downsizing	LSEG
Firm size	Firm_size	Control	The logarithm of the total assets	LSEG
Asset change	Asset_change	Control	Percentage of change in firms' total assets in the year the workforce reduction took place compared to the previous year	LSEG

Research ethics

This research was conducted under the Netherlands Code of Conduct for Research Integrity principles. Radboud University Nijmegen emphasises that research should follow the code of conduct described by the NWO. By following the code of conduct, researchers comply with the following principles: (1) Honesty, (2) Scrupulousness, (3) Transparency, (4) Independence and (5) Responsibility (NWO, 2018). Therefore, this research implies that all the data collected is reported without fabrication or falsification and will not be used for other purposes. Independence was maintained and literature was handled with their sources including APA references.

Analysis

Data preparation

The initial sample of this research contained 1106 firms, of which 571 had downsized at least 5% of their employees between 2010 and 2020, resulting in a total of 1095 observations. After deleting 30 observations because of extensive downsizing or abnormal values, 1065 observations remained present in the final sample. A more in-depth analysis is made by dividing the downsizing firms into three different magnitudes, as described by Brauer and Laamanen (2014). The small-scale downsizing sample consists of 570 observations and can be seen in table 5, the medium-scale downsizing sample consists of 303 observations, and lastly, the large-scale downsizing sample consists of 192 observations, which both can be found in Appendix D.

Descriptive statistics

Table 2 shows the descriptive statistics of the final data sample, containing 1065 observations. The table shows the mean, standard deviation, minimum values, maximum values, skewness and kurtosis. Some of the variables did not meet the preferred threshold of the skewness and kurtosis not exceeding |3|. Despite trying different transformations to account for this issue, none of them resulted in better fits of the values. Therefore, the decision was made not to transform the variables and continue with the analysis. The results for some of the tried transformations can be found in Appendix C.

Table 2: Descriptive statistics

Descriptive Statistics

Variables	n	mean	sd	min	max	skew	kurtosis	se
ROA_winsorized	1,065	1.141	6.322	-18.696	26.121	0.814	3.866	0.194
Downsizing	1,065	13.514	10.682	5.001	70.195	2.247	5.789	0.327
Digital	1,065	0.580	1.069	0	3	1.471	0.451	0.033
In_Health_care	1,065	0.061	0.240	0	1	3.662	11.422	0.007
In_Financial_RealEstate	1,065	0.210	0.408	0	1	1.420	0.015	0.012
In_Consumer_Discretionary	1,065	0.194	0.396	0	1	1.543	0.380	0.012
In_Industrials_and_materials	1,065	0.285	0.451	0	1	0.954	-1.091	0.014
In_Energy_and_utilities	1,065	0.143	0.350	0	1	2.040	2.163	0.011
Prior_performance	1,065	5.278	6.784	-39.617	53.970	0.374	10.924	0.208
Firm_size	1,065	16.859	1.685	11.064	22.442	-0.089	0.404	0.052
Asset_change	1,065	-0.006	0.131	-0.606	0.734	0.463	4.391	0.004

To examine the relationships between variables within the model, a correlation matrix was generated by using the Pearson correlation coefficient. Following Hair et al. (2019), no correlation should be above 0.90, as can be seen in Table 3, this rule was satisfied. To test for the multicollinearity of the dataset both the Variance Inflation Factor (VIF) and Tolerance were calculated for the independent variables, as can be seen in Table 4. The highest VIF value observed was 2.735, which is below the threshold of 5, indicating that no multicollinearity was present. Additionally, the tolerance of the independent variables was tested to make sure that there was no multicollinearity within the dataset, with no values being close to 0.1, there was no concern of multicollinearity within the dataset.

Table 3: Correlation matrix

Correlation Matrix

Variables	1	2	3	4	5	6	7	8	9	10	11
ROA_winsorized	1										
Downsizing	0.06	1									
Digital	0.02	-0.03	1								
In_Health_care	0.01	-0.02	-0.05	1							
In_Financial_RealEstate	-0.04	-0.05	-0.04	-0.13* * *	1						
In_Consumer_Discretionary	0.03	0.02	0.06	-0.13* * *	-0.25* * *	1					
In_Industrials_and_materials	-0.01	-0.03	-0.05	-0.16* * *	-0.33* * *	-0.31* * *	1				
In_Energy_and_utilities	-0.00	0.12* * *	-0.11* * *	-0.10* * *	-0.21* * *	-0.20* * *	-0.26* * *	1			
Prior_performance	-0.33* * *	-0.02	-0.01	0.02	-0.15* * *	0.17* * *	0.03	-0.10* * *	1		
Firm_size	-0.14* * *	-0.07*	-0.01	-0.02	0.33* * *	-0.13* * *	-0.15* * *	0.09* *	-0.12* * *	1	
Asset_change	-0.16* * *	-0.15* * *	-0.01	-0.01	0.07*	0.05	0.01	-0.11* * *	0.18* * *	-0.03	1

Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 4: VIF and Tolerance Values

VIF and Tolerance Values

	VIF	Tolerance
Downsizing	1.045	0.957
Digital	1.067	0.937
In_Health_care	1.523	0.657
In_Financial_RealEstate	2.670	0.375
In_Consumer_Discretionary	2.329	0.429
In_Industrials_and_materials	2.735	0.366
In_Energy_and_utilities	2.199	0.455
Prior_performance	1.095	0.913
Firm_size	1.171	0.854
Asset_change	1.076	0.930

Main results

The main results from the regression analysis can be found in Table 5.

Table 5: Regression analysis main results

Regression Results

	Dependent variable:			
	ROA_winsorized			
	(1)	(2)	(3)	(4)
Independent variable				
Downsizing	0.016	0.007	-0.002	-0.025
	(0.017)	(0.019)	(0.058)	(0.062)
Moderation variables				
Digital		-0.135		-0.191
		(0.276)		(0.290)
In_Health_care			-0.402	-0.505
			(1.543)	(1.562)
In_Financial_RealEstate			-1.494	-1.678
			(1.106)	(1.135)
In_Consumer_Discretionary			-0.356	-0.421
			(1.107)	(1.114)
In_Industrials_and_materials			-0.054	-0.179
			(1.058)	(1.080)
In_Energy_and_utilities			-0.666	-0.891
			(1.177)	(1.215)
Control variables				
Prior_performance	-0.314***	-0.315***	-0.330***	-0.331***
	(0.027)	(0.027)	(0.027)	(0.028)
Firm_size	-0.686***	-0.684***	-0.627***	-0.626***
	(0.107)	(0.107)	(0.114)	(0.115)
Asset_change	-4.836***	-4.762***	-4.806***	-4.697***
	(1.404)	(1.405)	(1.420)	(1.424)
Interaction effects				
Downsizing: Digital		0.019		0.019
		(0.017)		(0.018)
Downsizing: In_Health_care			0.030	0.040
			(0.100)	(0.100)
Downsizing: In_Financial_RealEstate			0.065	0.082
			(0.069)	(0.071)
Downsizing: In_Consumer_Discretionary			0.071	0.079
			(0.069)	(0.070)
Downsizing: In_Industrials_and_materials			-0.033	-0.021
			(0.068)	(0.069)
Downsizing: In_Energy_and_utilities			-0.009	0.012
			(0.069)	(0.071)
Constant	14.127***	14.145***	13.724***	13.946***
	(1.866)	(1.872)	(2.090)	(2.112)
Observations	1,065	1,065	1,065	1,065
R^2	0.155	0.157	0.167	0.168
Adjusted R^2	0.152	0.152	0.155	0.155
Residual Std. Error	5.822 (df = 1060)	5.822 (df = 1058)	5.810 (df = 1050)	5.812 (df = 1048)
F Statistic	48.734*** (df = 4; 1060)	32.786*** (df = 6; 1058)	14.989*** (df = 14; 1050)	13.187*** (df = 16; 1048)
Note:	*p<0.1; **p<0.05; ***p<0.01			

Model 1, the baseline model, represents the relationship between the dependent variable (*Return on assets)* and the independent variable (*Employee downsizing),* including all control variables (*Prior performance)*, (*Firm size)* and (*Asset change)*. The model shows that *Employee downsizing* has a positive non-significant coefficient (Model 1, β = 0.016, $p > 0.05$), indicating that *Employee downsizing* alone does not significantly impact *Return on assets*. Therefore, no support for hypothesis 1 is found in Model 1. Notably, in every model, the control variables, *Prior performance*, *Firm size* and *Asset change* are found to be significant. The significant negative coefficients suggest that firms with higher prior performance, larger firm size or bigger asset change are found to have lower returns on assets. These findings highlight the complexity of underlying relationships and emphasise the need for further research.

Model 2 introduces the moderating variable *Digitalization*. Model 2 shows that neither *Digitalization* nor its interaction with *Employee downsizing* has a significant effect on *Return on assets* (Model 2, $\beta = -0.135$, $p > 0.05$) (Model 2, $\beta = 0.019$, $p > 0.05$). Therefore, no support for hypothesis 2 was found in Model 2 of the main regression analysis.

Model 3 then includes the moderator industry fixed effects, industry dummy variables were added with industry *technology and telecom* serving as reference category. The coefficients for the different industries and their interactions with *Employee downsizing* are all found to be non-significant, thus finding no support for hypothesis 3.

Model 4 represents the full model with all variables and interaction effects included. *Employee downsizing* remains non-significant (Model 4, $\beta = -0.025$, $p > 0.05$), also the moderating variables and their interaction effects remain non-significant, failing to find support for the hypothesis. In conclusion, the main regression analysis did not provide valuable significant insights on the effects of employee downsizing, digitalization and industry-fixed factors on firm performance.

Additional analysis

To add more depth and robustness to the analysis, another regression analysis was conducted in which employee downsizing was divided into three different magnitudes following the research of Brauer & Laamanen (2014). The regression results of small-scale downsizing can be found in table 6, the regression results of medium-scale and large-scale downsizing can be found in Appendix D.

Table 6: Regression analysis of small-scale downsizing

Regression Results small-scale downsizing

	Dependent variable:			
	ROA_winsorized			
	(1)	(2)	(3)	(4)
Independent variable				
Downsizing	-0.328**	-0.249	-1.342***	-1.343***
	(0.144)	(0.166)	(0.388)	(0.437)
Moderating variables				
Digital		0.867		-0.082
		(0.924)		(0.973)
In_Health_care			-5.034	-5.033
			(5.117)	(5.213)
In_Financial_RealEstate			-12.101***	-12.124***
			(3.551)	(3.651)
In_Consumer_Discretionary			-5.737	-5.672
			(3.699)	(3.746)
In_Industrials_and_materials			-9.712***	-9.736***
			(3.325)	(3.467)
In_Energy_and_utilities			-4.695	-4.761
			(4.034)	(4.151)
Control variables				
Prior_performance	-0.228***	-0.229***	-0.244***	-0.244***
	(0.030)	(0.030)	(0.031)	(0.031)
Firm_size	-0.438***	-0.441***	-0.359***	-0.358***
	(0.118)	(0.119)	(0.124)	(0.124)
Asset_change	-1.703	-1.649	-1.145	-1.126
	(1.906)	(1.909)	(1.921)	(1.926)
Interaction effects				
Downsizing: Digital		-0.124		0.006
		(0.130)		(0.137)
Downsizing: In_Health_care			0.621	0.616
			(0.715)	(0.733)
Downsizing: In_Financial_RealEstate			1.641***	1.639***
			(0.503)	(0.520)
Downsizing: In_Consumer_Discretionary			0.895*	0.884*
			(0.518)	(0.528)
Downsizing: In_Industrials_and_materials			1.378***	1.377***
			(0.466)	(0.490)
Downsizing: In_Energy_and_utilities			0.533	0.537
			(0.561)	(0.578)
Constant	11.650***	11.165***	17.727***	17.773***
	(2.298)	(2.361)	(3.428)	(3.644)
Observations	570	570	570	570
R^2	0.114	0.116	0.146	0.146
Adjusted R^2	0.108	0.106	0.124	0.121
Residual Std. Error	4.864 (df = 565)	4.868 (df = 563)	4.819 (df = 555)	4.827 (df = 553)
F Statistic	18.188*** (df = 4; 565)	12.256*** (df = 6; 563)	6.765*** (df = 14; 555)	5.902*** (df = 16; 553)
Note:	*p<0.1; **p<0.05; ***p<0.01			

Model 1, the baseline model for small-scale downsizing, shows a surprisingly significant negative relationship between *small-scale downsizing* and *firm performance* (Model 1, β = -0.328, p < 0.05). Contrary, the medium (Model 1, β = -0.159, p > 0.1) and large-scale (Model 1, β = - 0.016, p > 0.1) models (appendix D) showed no sign of significant relationships. The findings suggest that the negative effects of employee downsizing on firm performance are more pronounced within firms that apply small-scale downsizing. Therefore, there is partial support for hypothesis 1, which states that the magnitude of employee downsizing is negatively related to firm performance.

Model 2, which introduces the moderator *Digitalization* for small-scale downsizing, shows that neither *Digitalization* nor its interaction effect with *Employee downsizing* is significant (Model 2, $\beta = 0.867$, $p > 0.1$). This observation remains present within the analysis of medium (Model 2, $\beta = -0.135$, $p > 0.1$) and large-scale downsizing (Model 2, $\beta = -0.425$, $p > 0.1$). Hypothesis 2 stated that *Digitalization* would positively moderate the effects of *Employee downsizing* on *Firm performance*. With no significant findings in both the main regression analysis and across the different magnitudes of downsizing, hypothesis 2 is rejected.

Model 3 includes the moderator industry fixed effects. While the results within the main regression (table 5) showed no significant industry interaction effects, further analysis of different magnitudes revealed significant findings for some industries. Within model 3 of small-scale downsizing firms, both *In_Financial_RealEstate* (Model 3, $\beta = -12.101$, $p < 0.01$) as its interaction effect with *Employee downsizing* (Model 3, $\beta = 1.641$, $p < 0.01$) are of significant effect on *Return on assets.* In addition, also *In_Industrials_and_materials* (Model 3, $\beta = -9.712$, $p < 0.01$) and its interaction effect with *Employee downsizing* (Model 3, $\beta = 1.378$, $p < 0.01$) have a significant effect on *Return on assets*. The significant interaction effects indicate that the negative effects of small-scale downsizing on firm performance are less severe in the *Financial real estate* and *Industrials and materials* industries compared to the reference industry, *Technology and telecom*. The medium and large-scale models (Appendix D) showed no significant interaction effects. Therefore, hypothesis 3 is only partly rejected since the findings were not consistently observed across all magnitudes of downsizing and the expected negative moderation effects were found to be positive in specific industries.

Model 4, the full model including all variables and interaction effects, shows that the negative effect of *Employee downsizing* on *Firm performance* became more significant within small-scale downsizing (Model 4, $\beta = -1.343$, $p < 0.01$) compared to (Model 1, $\beta = -0.328$, $p < 0.05$). The increased negative coefficient ($\beta = -1.343$) indicates that when all important variables and interaction effects are present, the negative impact of *Employee downsizing* on *Firm performance* is even more pronounced. Furthermore, the R-squared for Model 4 ($R^2 = 0.146$) compared to Model 1 ($R^2 = 0.114$) slightly increased, indicating a better model fit and greater explanatory power. Within the medium and large-scale downsizing (Appendix D) none of the significance changed.

Robustness

To make sure that all the interaction effects were adequately captured, an additional robustness check was constructed in which every regression model isolates each interaction effect against the background of the baseline model as can be seen in Table 7.

Model 1 represents the base model. Models 2 to 6 each include a different moderating variable to look for independent effects. Model 4, which includes *In_Financial_RealEstate*, shows a small significant effect (Model 4, $\beta = -1.180$, $p < 0.1$). Model 6, in which *In_industrials_and_materials* is added, shows a small negative significant interaction effect with *Employee downsizing* (Model 6, $\beta = -0.067$, $p < 0.1$). The robustness check reveals that within the industry *Industrials_and_materials,* downsizing has a more negative impact on firm performance compared to the reference category, *Technology and telecom.* This observed effect is contrary to the positive interaction effect within model 3 (table 6) in the context of small-scale downsizing, suggesting that industry-specific factors fluctuate across the different downsizing magnitudes.

To check for a possible non-linear relationship between employee downsizing and firm performance, both quadratic and cubic polynomials were added to capture potential non-linearity as can be seen in Appendix E. Although the presence of a small curvature, statistical results did not indicate the presence of a non-linear effect. Table 8 shows a summary of the hypothesised relationships and empirical conclusions.

Table 7: Regression analysis with isolated interaction effects

Regression Results

	Dependent variable:						
	ROA_winsorized						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent variable							
Downsizing	0.016	0.007	0.015	0.004	0.001	0.030	0.027
	(0.017)	(0.019)	(0.017)	(0.019)	(0.019)	(0.019)	(0.019)
Moderating variables							
Digital		-0.135					
		(0.276)					
In_Health_care			0.113				
			(1.293)				
In_Financial_RealEstate				-1.180*			
				(0.714)			
In_Consumer_Discretionary					0.156		
					(0.730)		
In_Industrials_and_materials						0.553	
						(0.660)	
In_Energy_and_utilities							-0.061
							(0.821)
Control variables							
Prior_performance	-0.314***	-0.315***	-0.314***	-0.318***	-0.324***	-0.314***	-0.317***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Firm_size	-0.686***	-0.684***	-0.685***	-0.651***	-0.661***	-0.705***	-0.672***
	(0.107)	(0.107)	(0.107)	(0.113)	(0.107)	(0.108)	(0.107)
Asset_change	-4.836***	-4.762***	-4.816***	-4.716***	-4.886***	-4.778***	-5.043***
	(1.404)	(1.405)	(1.407)	(1.411)	(1.400)	(1.403)	(1.409)
Interaction effects							
Downsizing: Digital		0.019					
		(0.017)					
Downsizing: In_Health_care			0.012				
			(0.082)				
Downsizing: In_Financial_RealEstate				0.058			
				(0.042)			
Downsizing: In_Consumer_Discretionary					0.067		
					(0.041)		
Downsizing: In_Industrials_and_materials						-0.067*	
						(0.040)	
Downsizing: In_Energy_and_utilities							-0.039
							(0.040)
Constant	14.127***	14.145***	14.102***	13.806***	13.733***	14.339***	13.844***
	(1.866)	(1.872)	(1.870)	(1.926)	(1.884)	(1.909)	(1.875)
Observations	1,065	1,065	1,065	1,065	1,065	1,065	1,065
R^2	0.155	0.157	0.155	0.158	0.162	0.158	0.157
Adjusted R^2	0.152	0.152	0.151	0.153	0.157	0.153	0.153
Residual Std. Error	5.822 (df = 1060)	5.822 (df = 1058)	5.827 (df = 1058)	5.820 (df = 1058)	5.804 (df = 1058)	5.818 (df = 1058)	5.820 (df = 1058)
F Statistic	48.734*** (df = 4; 1060)	32.786*** (df = 6; 1058)	32.457*** (df = 6; 1058)	32.976*** (df = 6; 1058)	34.062*** (df = 6; 1058)	33.114*** (df = 6; 1058)	32.938*** (df = 6; 1058)
Note:	*p<0.1; **p<0.05; ***p<0.01						

Hypothesis	Expected relationship	Empirical conclusion
H1: *The magnitude of employee downsizing is negatively related to firm performance.*	-	Partly supported
H2: *Digitalization positively moderates the effects of employee downsizing on firm performance*	+	Unsupported
H3: Industry characteristics negatively moderate the relationship between employee downsizing and firm performance	-	Partly rejected

Table 8: Summary of hypothesis

Discussion

This research used the resource-based view as a theoretical framework to better understand the impact of employee downsizing on firm performance in the context of digitalization and industry characteristics. Previous research that examined the impact of employee downsizing on firm performance resulted in mixed findings due to different contextual factors that influence downsizing outcomes (Brauer & Laamanen, 2014; Cascio et al., 2021; Datta & Basuil, 2015). Despite the growing interest from organisations and researchers on the effects of employee downsizing due to evolving business environments, little attention has been paid on how these effects interact with the increasing adoption of digital technologies. Therefore, this research aims to fill the gap by looking into how digitalization and industry characteristics can influence the relationship between employee downsizing and firm performance by addressing the following research question:

Does the magnitude of employee downsizing influence firm performance, and what is the role of digitalization and industry characteristics on this relationship?

Based on a sample of 1065 observations derived from 571 unique international firms that engaged in downsizing, limited support has been found for the developed hypothesis, with only marginal significance observed in the various regression models. Contrary to the expectations of observing a profound negative relationship between all magnitudes of employee downsizing and firm performance, as well as the moderating effects of industry characteristics and digitalization, the regression models showed only limited significant results. The results of this research suggest that the relationship between employee downsizing and firm performance is complex and not only determined by employee downsizing alone, which aligns with the mixed findings in the literature (Datta & Basuil, 2015).

Interestingly, a significant negative relationship was observed within small-scale downsizing firms and firm performance. These findings suggest that small-scale downsizing might be more disruptive than anticipated, possibly due to small reductions not being accompanied by strategic planning or the support of remaining employees (Love & Nohria, 2005). These findings were non-consistent for medium- and large-scale downsizing firms and contrary to prior literature by Brauer & Laamanen (2014), which found significant positive effects of small-scale downsizing. Additionally, digitalization did not significantly moderate the relationship between downsizing and firm performance. However, within small-scale downsizing firms, the industries' *financial real estate* and *industrials and materials* were found to significantly moderate the negative effects of employee downsizing on firm performance, amplifying the need for further research on how this complex relationship develops within different contexts.

Theoretical implications

This research contributes to the understanding of the relationship between employee downsizing and financial performance and leaves several paths for further research. Firstly, the findings emphasise the complexity of capturing the relationship between the magnitude of employee downsizing and firm performance. The findings highlight that small-scale downsizing has a more pronounced negative impact on firm performance than medium- and large-scale downsizing. This implies that small-scale downsizing might be more disruptive than prior research initially suggested. As mentioned earlier, an explanation of this complexity could be the lack of strategic planning, an absence of support, or a loss of critical knowledge that is associated with small-scale downsizing (Appelbaum et al., 1999; Datta et al., 2010; Love & Nohria, 2005).

While specific reasons behind the negative results of employee downsizing show limited agreement, consistent findings emphasise that negative outcomes often relate to hidden costs and beaches in psychological contracts where employees feel that their contract agreements have been breached by their employer (Aalbers & Dolfsma, 2019; Kao & Chen, 2020; Kim et al., 2024). When small numbers of employees are laid off, concerns about job insecurities rise, amplifying the negative effects of employee downsizing. Additionally, small-scale downsizing, especially during times of market expansion, could be seen as less legitimate, which negatively impacts employee morale and commitment, thereby reducing organisational effectiveness (Guthrie & Datta, 2008; Datta & Basuil, 2015). These findings challenge the traditional view of small-scale downsizing as being less harmful to firm performance, emphasising the need for careful consideration and assessment of both eternal factors as strategic planning when engaging in downsizing.

Secondly, this research incorporates digitalization as a potential moderator, refining the resource-based view. While no significant results were found for the moderating effect of digitalization on the relationship between downsizing and firm performance, the theoretical frameworks support the capabilities of digital technology to enhance operational efficiency, innovation and internal communication (Bharadwaj et al., 2013; Hess et al., 2016; Sebastian et al., 2020). The non-significant findings could be attributed to a decision-making mismatch that hinders the effective utilization of digital technologies within incumbent firms, especially during times of downsizing. Research has shown that the digital transformation of incumbent business models is highly complex and requires both calculated and interdependent strategic decisions to be successful. Challenges arise when managers, who tend to make decisions based on prior experience, engage in decision-making over unfamiliar options, resulting in a managing mismatch between the new economic reality and the old established business models (Verhoef et al., 2021; Warner & Wäger, 2019).

In addition, to leverage digital benefits, organisations must strive for digital maturity, an ongoing process of adapting to the changing digital landscape. Digital maturity is not solely about adopting new technologies but about integrating technologies into existing business processes to create flexibility, responsiveness, capture knowledge and stimulate collaboration to overcome the common barriers of functional silos. To fully leverage the benefits of digitalization, organisations must achieve and strive for a certain level of digital maturity (Kane et al., 2017; Warner & Wäger, 2019). The findings suggest that digitalization is hard to leverage and difficult to capture in the context of employee downsizing. Theory posits that digitalization can create competitive advantages, capture knowledge and mitigate negative effects when other factors are threatening firm performance, but only when firms actively try to incorporate digital technologies within their business operations (Céspedes-Lorente et al., 2019; Sebastian et al., 2020). The observed non-significant moderating effects of digitalization could thus be attributed to the absence of digital maturity or insufficient integration of digital technologies within the whole business model.

Third and finally, this research reinforces the context-dependent nature of downsizing outcomes, as prior research already suggested (Cascio, 2002; Guthrie & Datta, 2008; Kao & Chen, 2020). Industry-specific characteristics appeared to have a significant moderating effect in determining how effective downsizing outcomes develop within specific sectors, e.g. *Financial Real Estate* and *Industrials and Materials* as compared to the reference industry *Technology and Telecom*. The findings suggest that firms in *Financial Real Estate* and *Industrials and Materials* might possess unique capabilities or face specific environmental conditions that mitigate the negative financial impact of employee downsizing compared to the reference category. The results, however, did not confirm prior empirical findings that rapidly evolving R&D-intensive industries such as biotechnology and pharmaceuticals are more sensitive to downsizing efforts due to the loss of critical human and social capital (Guthrie & Datta, 2008; Kao & Chen, 2020).

Practical implications

This research offers valuable implications for managers and policymakers involved in strategic decision-making, especially concerning employee downsizing in the context of digitalization and industry-specific characteristics. Firstly, managers should consider the importance of strategic planning when engaging in employee downsizing regardless of the magnitude. The significant negative findings in small-scale downsizing suggest that even small-scale downsizing can disrupt existing relationships, damaging human capital and negatively impacting the firm's performance. Companies should decide to downsize only when the actions are supported by strategic planning and clear communication to mitigate negative effects on firm performance (Aalbers, 2020; Guthrie & Datta, 2008; Love & Nohria, 2005; Norman et al., 2013).

Secondly, managers should recognise industry-specific characteristics when downsizing. This research indicates that industry-specific factors could either amplify or deteriorate downsizing outcomes. Managers should adapt their downsizing strategies to their unique industry context in an effort to mitigate the nonbeneficial effects of employee downsizing on firm performance.

Thirdly, although this research did not find significance in the moderating effects of digitalization, the potential benefits surrounding digital technologies in enhancing firms' competitive advantages and moderating the relationship between employee downsizing and firm performance are well supported by the literature (Sebastian et al., 2020). Managers should acknowledge the opportunities that come with digital technologies and start by striving for digital maturity by developing clear strategies that allow firms to implement and exploit digital technologies to achieve future business success (Hess et al., 2016; Kane et al., 2017; Sebastian et al., 2020). Digital technologies allow firms to extend their organisational memory making it possible to capture tacit knowledge which can be leveraged when firms decide to engage in employee downsizing, making them more resilient to the loss of critical knowledge (Céspedes-Lorente et al., 2019; Kuusisto, 2017).

Limitations and future research

This thesis is subjected to several limitations that need to be recognized and pointed out so they can be examined within future research. First of all, due to the lack of data on R&D expenses and other industry variables, this study was forced to capture industry characteristics as a fixed factor. Future research should focus on gathering this financial data which allows for a better understanding on how and which specific industry characteristics influence the relationship between employee downsizing and firm performance.

Secondly, as this study tried to assess digitalization through regular expression, there are some limitations associated with this method. This relatively new way of analysing allowed for analysing over 10.000 annual reports in a matter of days but has merely been used to assess and capture digitalization, leaving some open ends. Literature also emphasized that digitalization is an ongoing process which involves strategic planning and striving for digital maturity to fully leverage its potential (Kane et al., 2017; Warner & Wäger, 2019). This study did not determine the level of digital maturity within the sample firms to assess whether the digital systems were fully integrated and capable of mitigating the negative effects of employee downsizing.

Future research should build upon the dictionary developed within this research, expanding it to capture a broader range of regular expressions that determine digitalization. It is possible that valuable regular expressions associated with digitalization were not captured with the dictionary used in this research, given the non-significant findings, limiting the generalizability of these findings. Future research that tries to assess and capture the level of digitalization within firms should look for a combination of qualitative and quantitative methods. The most robust way of capturing digitalization is done by assessment from within the firm through interviews or a survey with managers (Zeng et al., 2022). By asking questions that relate to whether digital technologies are implemented, how they capture knowledge, and which specific technologies are used, a more reliable determination of the level of digitalization can be made. By converting the output into a dictionary for text analysis and combining those results with relevant company data and digital metrics such as IT expenditure and the number of digital projects, digitalization can be captured more precisely (Verhoef et al., 2021). The gathered information can then be used to capture digitalization in a bigger sample of firms and determine how the relationship between digitalization, employee downsizing, and firm performance evolves.

Thirdly, this thesis only focused on the impact on return on assets (ROA) to analyse the impact of employee downsizing. Downsizing is often accompanied by big asset divestitures, making it difficult to isolate the effect of employee downsizing on firm performance. The significant negative findings for small-scale downsizing emphasize the need for further investigation of this complex relationship. Moreover, this thesis did not account for the type of downsizing, which is argued to influence the downsizing outcomes(Céspedes-Lorente et al., 2019; Datta & Basuil, 2015). Future research could examine the various downsizing types within the context of digitalization and industry characteristics to provide a more refined understanding of this complex relationship.

Conclusion

This research investigated the effect of employee downsizing on firm performance in the context of digitalization and industry characteristics. By doing so, this research tried to address the gap in understanding how digitalization and specific industry factors influence the relationship on firm performance. The resource-based view was used as a theoretical lens, which states that post-downsizing effectiveness is determined by the presence and utilization of unique resources that can be leveraged to create competitive advantages (Barney, 1991; Chen et al., 2021).

Contrary to the expectations, the regression results showed only limited significant effects. The findings revealed that small-scale downsizing has a significant negative impact on firm performance, which was contrary to prior research. Digitalization, against expectations, did not significantly moderate the effect of employee downsizing on firm performance while its potential to do so seemed well supported in the literature. Furthermore, some industry-specific characteristics were found to significantly moderate the negative effects of employee downsizing, emphasising the importance of contemplating external factors when engaging in downsizing. This research provides new insights into the complex relationship between employee downsizing and firm performance and the influence of external factors. The findings will hopefully provide actionable knowledge that will encourage future research to dive into this versatile topic and enable organisations to be more successive when engaging in downsizing practices.

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Appendix A. Regular expressions Digitalization

Key words digitalization	**Regular expressions**
Adaptive learning	\b[A-Z][^.?!]*\badaptive learning\b[^.?!]*[.?!]
AI (Artificial intelligence)	\b[A-Z][^.?!]*\bartificial intelligence\b[^.?!]*[.?!]
APIs ()	\b[A-Z][^.?!]*\b(?:APIs|Application Programming Interfaces)\b[^.?!]*[.?!]
Big data	\b[A-Z][^.?!]*\bbig data\b[^.?!]*[.?!]
Blockchain + Technology or management	\b[A-Z][^.?!]*\bBlockchain\b[^.?!]*\b(?:technology|management)\b[^.?!]*[.?!]
Cloud + (Technology or Storage or Platform)	\b[A-Z][^.?!]*\bCloud\b[^.?!]*\b(?:Technology|Storage|Platform)\b[^.?!]*[.?!]
Cloud computing	\b[A-Z][^.?!]*\bCloud computing\b[^.?!]*[.?!]
Customer relationship management (CRM)	\b[A-Z][^.?!]*\b(?:Customer Relationship Management|CRM)\b[^.?!]*[.?!]
Cybersecurity	\b[A-Z][^.?!]*\b(?:Customer Relationship Management|CRM)\b[^.?!]*[.?!]
Data + (Analysis or Mining or Visualisation or Lake)	\b[A-Z][^.?!]*\bdata\b[^.?!]*\b(?:analysis|mining|visualisation|lake)\b[^.?!]*[.?!]
Data mesh	\b[A-Z][^.?!]*\bdata mesh\b[^.?!]*[.?!]
Deep learning	\b[A-Z][^.?!]*\bdeep learning\b[^.?!]*[.?!]
Digital + (Data or Marketing or strategy or transformation or (r) evolution)	\b[A-Z][^.?!]*\bdigital\b[^.?!]*\b(?:data|marketing|strategy|transformation|revolution)\b[^.?!]*[.?!]
Digital twin	\b[A-Z][^.?!]*\bdigital twin\b[^.?!]*[.?!]
Digitalization / Digitalisation / Digitization	\b[A-Z][^.?!]*\b(?:digitalization|digitalisation|digitization)\b[^.?!]*[.?!]
DevOps (Development&Operations)	\b[A-Z][^.?!]*\bDevOps\b[^.?!]*[.?!]
Enterprise resource planning (ERP)	\b[A-Z][^.?!]*\b(?:enterprise resource planning|ERP)\b[^.?!]*[.?!]
Human-computer	\b[A-Z][^.?!]*\bhuman[^.?!]*computer\b[^.?!]*[.?!]

<table>
<tr><td>Intelligent + (logistics or management or manufacturing or office or service or supply chain)</td><td>\b[A-Z][^.?!]*\bintelligent\b[^.?!]*\b(?:logistics|management|manufacturing|office|service|supply chain)\b[^.?!]*[.?!]</td></tr>
<tr><td>Internet of (everything or things)</td><td>\b[A-Z][^.?!]*\binternet of\b[^.?!]*\b(?:everything|things)\b[^.?!]*[.?!]</td></tr>
<tr><td>Web3</td><td>\b[A-Z][^.?!]*\bWeb3\b[^.?!]*[.?!]</td></tr>
<tr><td>Machine learning</td><td>\b[A-Z][^.?!]*\bmachine learning\b[^.?!]*[.?!]</td></tr>
<tr><td>Online customer service</td><td>\b[A-Z][^.?!]*\bonline[^.?!]*customer service\b[^.?!]*[.?!]</td></tr>
<tr><td>Predictive analytics</td><td>\b[A-Z][^.?!]*\bpredictive analytics\b[^.?!]*[.?!]</td></tr>
<tr><td>Quantum computing</td><td>\b[A-Z][^.?!]*\bquantum computing\b[^.?!]*[.?!]</td></tr>
<tr><td>Data visualization</td><td>\b[A-Z][^.?!]*\bdata visualization\b[^.?!]*[.?!]</td></tr>
<tr><td>Digital Investments</td><td>\b[A-Z][^.?!]*\bdigital investments\b[^.?!]*[.?!]</td></tr>
<tr><td>E-commerce</td><td>\b[A-Z][^.?!]*\bE-commerce\b[^.?!]*[.?!]</td></tr>
<tr><td>Digital Customer Experience</td><td>\b[A-Z][^.?!]*\bdigital customer experience\b[^.?!]*[.?!]</td></tr>
<tr><td>Business intelligence</td><td>\b[A-Z][^.?!]*\bbusiness intelligence\b[^.?!]*[.?!]</td></tr>
<tr><td>Customer Journey Tracking</td><td>\b[A-Z][^.?!]*\bcustomer journey tracking\b[^.?!]*[.?!]</td></tr>
<tr><td>Augmented reality</td><td>\b[A-Z][^.?!]*\baugmented reality\b[^.?!]*[.?!]</td></tr>
<tr><td>Cyber physical systems (CPS)</td><td>\b[A-Z][^.?!]*\b(?:cyber-physical systems|CPS)\b[^.?!]*[.?!]</td></tr>
<tr><td>Rami 4.0</td><td>\b[A-Z][^.?!]*\bRami 4.0\b[^.?!]*[.?!]</td></tr>
<tr><td>Cyber Physical production system (CPPS)</td><td>\b[A-Z][^.?!]*\b(?:cyber-physical production system|CPPS)\b[^.?!]*[.?!]</td></tr>
<tr><td>Machine to machine (M2M)</td><td>\b[A-Z][^.?!]*\b(?:machine to machine|M2M)\b[^.?!]*[.?!]</td></tr>
<tr><td>Embedded system</td><td>\b[A-Z][^.?!]*\bembedded system\b[^.?!]*[.?!]</td></tr>
<tr><td>Software as a service (SaaS)</td><td>\b[A-Z][^.?!]*\b(?:software as a service|SaaS)\b[^.?!]*[.?!]</td></tr>
<tr><td>Cyber intelligence</td><td>\b[A-Z][^.?!]*\bcyber intelligence\b[^.?!]*[.?!]</td></tr>
</table>

Appendix B. Digitalization expressions ranking scheme by year

Year	10	11	12	13	14	15	16	17	18	19	20
Adaptive learning	1	1	1	1	2	2	2	2	2	2	2
AI (Artificial intelligence)	2	2	2	2	3	3	3	3	3	3	3
APIs ()	3	3	3	3	3	3	3	3	2	2	2
Big data	3	3	3	3	3	3	3	3	2	2	2
Blockchain + Technology or management	3	3	3	2	2	2	2	2	2	2	2
Cloud + (Technology or Storage or Platform)	3	3	3	3	3	3	2	2	2	1	1
Cloud computing	3	3	3	3	3	3	3	3	3	3	3
Customer relationship management (CRM)	3	3	3	2	2	2	2	1	1	1	1
Cybersecurity	2	2	2	2	2	2	2	2	2	2	2
Data + (Analysis or Mining or Visualisation or Lake)	2	2	2	2	2	2	2	2	2	2	2
Data mesh	1	1	1	1	1	1	2	2	3	3	3
Deep learning	3	3	3	3	3	3	3	2	2	2	2
Digital + (Data or Marketing or strategy or transformation or (r) evolution)	2	2	2	2	2	2	2	2	2	2	2
Digital twin	3	3	3	3	3	3	3	3	3	3	3
Digitalization / Digitalisation / Digitization	2	2	2	2	2	2	1	1	1	1	1
DevOps (Development&Operations)	2	2	2	2	2	2	2	2	2	2	2
Enterprise resource planning (ERP)	3	3	3	2	2	2	2	1	1	1	1
Human-computer	1	1	1	1	1	1	1	1	1	1	1
Intelligent + (logistics or management or manufacturing or office or service or supply chain)	2	2	2	2	2	2	2	2	2	2	2

Internet of (everything or things)	3	3	3	3	3	3	3	2	2	2	2
Web3	3	3	3	3	3	3	3	3	3	3	3
Machine learning	3	3	3	3	3	3	3	2	2	2	2
Online customer service	3	3	3	2	2	2	2	1	1	1	1
Predictive analytics	3	3	3	3	3	3	3	3	3	3	3
Quantum computing	3	3	3	3	3	3	3	3	3	3	3
Data visualization	2	2	2	2	2	2	2	2	2	2	2
Digital Investments	2	2	2	2	2	2	2	2	2	2	2
E-commerce	3	3	3	2	2	2	2	1	1	1	1
Digital Customer Experience	3	3	3	2	2	2	2	1	1	1	1
Business intelligence	3	3	3	3	3	3	3	3	2	2	2
Customer Journey Tracking	3	3	3	2	2	2	2	1	1	1	1
Augmented reality	3	3	3	3	3	3	3	2	2	2	2
Cyber physical systems (CPS)	3	3	3	3	3	3	3	3	3	3	3
Rami 4.0	2	2	2	2	2	2	2	2	2	2	2
Cyber Physical production system (CPPS)	2	2	2	2	2	2	2	2	2	2	2
Machine to machine (M2M)	2	2	2	2	2	2	1	1	1	1	1
Embedded system	2	2	2	2	2	2	2	2	2	2	2
Software as a service (SaaS)	3	3	3	3	2	2	2	2	1	1	1
Cyber intelligence	3	3	3	3	2	2	1	1	1	1	1

Appendix C. Assumption checks

With a sample size of 1065 observations, the recommended threshold of 20:1 was clearly met. To conduct the multiple regression analysis four necessary assumptions had to be checked, linearity, homoscedasticity, normal distribution of error terms and independence of predicted value. Both linearity and homoscedasticity were checked using the scatterplot in table 9. As can be seen in table 9 there is no curvilinear pattern, the variation of the residuals also appears to be the same meaning that both the assumption of linearity and homoscedasticity have been met. To assess the third assumption of normal distribution of error terms, a probability plot was made, to satisfy the assumption, the dots must be close to the red dotted line within the plot. As can be seen in table 10 the dots in general stay close to the red dotted line which means that the third assumption has also been met. The last assumption, independence of predicted values, was tested by conducting the Durbin Watson test which should be non-significant to satisfy the assumption. With the D-W statistic of 1.970716 and a non-significant p-value of 0.301297 this assumption was also met. With all assumption satisfied, the multiple regression analysis can be conducted (Hair et al., 2019).

Table 9: Scatterplot

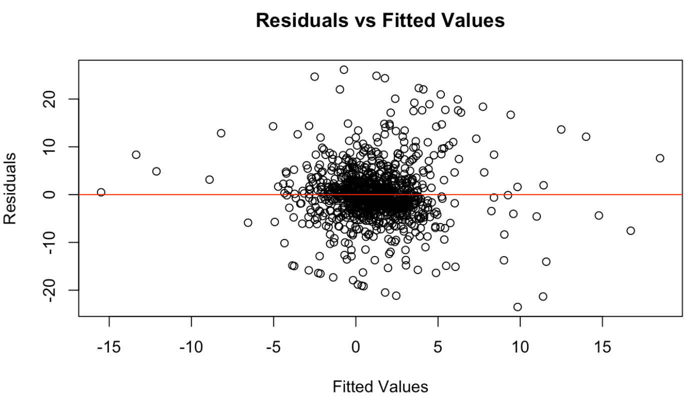

Table 10: P-P plot

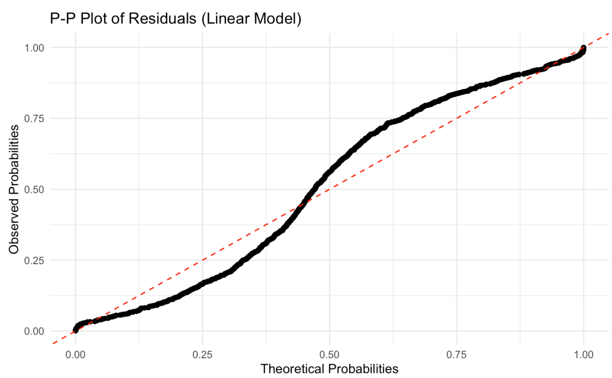

Table 11: Variable transformations

ROA_ln	ROA_ln	-4.890	73.516
ROA_yj	ROA_yj	0.600	14.390
Prior_performance	Prior_performance	0.374	13.950
Prior_performance_ln	Prior_performance_ln	-6.543	98.498

Appendix D. Magnitude of employee downsizing regression results

Regression Results medium-scale downsizing

	Dependent variable:			
	ROA_winsorized			
	(1)	(2)	(3)	(4)
Independent variable				
Downsizing	-0.159	-0.103	-0.139	-0.013
	(0.134)	(0.153)	(0.367)	(0.402)
Moderating variables				
Digital		1.809		1.853
		(1.825)		(1.880)
In_Health_care			15.861*	17.477*
			(8.854)	(9.035)
In_Financial_RealEstate			1.433	2.930
			(7.034)	(7.190)
In_Consumer_Discretionary			1.686	2.531
			(7.051)	(7.125)
In_Industrials_and_materials			0.677	1.994
			(6.689)	(6.859)
In_Energy_and_utilities			-9.580	-7.834
			(7.566)	(7.768)
Control variables				
Prior_performance	-0.470***	-0.467***	-0.487***	-0.482***
	(0.063)	(0.063)	(0.064)	(0.064)
Firm_size	-1.081***	-1.078***	-1.030***	-1.033***
	(0.237)	(0.238)	(0.264)	(0.266)
Asset_change	-8.560***	-8.600***	-7.632***	-7.740***
	(2.762)	(2.766)	(2.825)	(2.831)
Interaction effects				
Downsizing: Digital		-0.108		-0.111
		(0.124)		(0.128)
Downsizing: In_Health_care			-1.079*	-1.178*
			(0.623)	(0.636)
Downsizing: In_Financial_RealEstate			-0.197	-0.286
			(0.484)	(0.494)
Downsizing: In_Consumer_Discretionary			-0.052	-0.100
			(0.483)	(0.489)
Downsizing: In_Industrials_and_materials			-0.119	-0.201
			(0.457)	(0.471)
Downsizing: In_Energy_and_utilities			0.657	0.554
			(0.495)	(0.509)
Constant	24.130***	23.162***	23.247***	21.176***
	(4.570)	(4.751)	(7.499)	(7.945)
Observations	303	303	303	303
R^2	0.259	0.262	0.296	0.299
Adjusted R^2	0.249	0.247	0.262	0.260
Residual Std. Error	6.690 (df = 298)	6.699 (df = 296)	6.634 (df = 288)	6.644 (df = 286)
F Statistic	26.078*** (df = 4; 298)	17.536*** (df = 6; 296)	8.646*** (df = 14; 288)	7.618*** (df = 16; 286)
Note:	*p<0.1; **p<0.05; ***p<0.01			

Regression Results large-scale downsizing

	Dependent variable:			
	ROA_winsorized			
	(1)	(2)	(3)	(4)
Independent variable				
Downsizing	-0.016	-0.024	-0.079	-0.117
	(0.043)	(0.047)	(0.164)	(0.177)
Moderating variables				
Digital		-0.425		-0.435
		(1.597)		(1.691)
In_Health_care			-5.563	-5.804
			(9.827)	(9.891)
In_Financial_RealEstate			-0.622	-1.619
			(6.346)	(6.557)
In_Consumer_Discretionary			-7.720	-8.021
			(6.423)	(6.519)
In_Industrials_and_materials			3.476	3.017
			(6.411)	(6.546)
In_Energy_and_utilities			-4.087	-4.869
			(6.144)	(6.429)
Control variables				
Prior_performance	-0.355***	-0.362***	-0.398***	-0.402***
	(0.073)	(0.074)	(0.077)	(0.078)
Firm_size	-0.925***	-0.887***	-0.988***	-0.975***
	(0.324)	(0.325)	(0.350)	(0.351)
Asset_change	-3.106	-2.750	-2.583	-2.185
	(3.249)	(3.268)	(3.413)	(3.458)
Interaction effect				
Downsizing: Digital		0.033		0.028
		(0.049)		(0.053)
Downsizing: In_Health_care			0.177	0.192
			(0.298)	(0.300)
Downsizing: In_Financial_RealEstate			0.056	0.097
			(0.187)	(0.196)
Downsizing: In_Consumer_Discretionary			0.272	0.288
			(0.193)	(0.196)
Downsizing: In_Industrials_and_materials			-0.153	-0.130
			(0.195)	(0.200)
Downsizing: In_Energy_and_utilities			0.066	0.105
			(0.181)	(0.192)
Constant	19.724***	19.072***	23.326***	23.814***
	(5.717)	(5.785)	(7.664)	(8.013)
Observations	192	192	192	192
R^2	0.149	0.158	0.217	0.222
Adjusted R^2	0.130	0.130	0.156	0.151
Residual Std. Error	6.858 (df = 187)	6.858 (df = 185)	6.759 (df = 177)	6.777 (df = 175)
F Statistic	8.160*** (df = 4; 187)	5.775*** (df = 6; 185)	3.512*** (df = 14; 177)	3.120*** (df = 16; 175)
Note:	*p<0.1; **p<0.05; ***p<0.01			

Appendix E. Assessment of non-linearity