

Learning From Experience? The Impact of Restructuring Experience on a Firm's Digital

Innovation Performance

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Abstract: Digital innovation is essential for firms to survive in current industrial developments. Firms can increase their digital innovation performance by either developing it internally or by conducting digital M&A to acquire it from other firms. Although firms want to grow and improve their digital innovation performance, there seems to be no escaping from employee downsizing. Downsizing has shown to be of influence on a firm's post-downsizing performance. However, the impact that earlier downsizing experience can have on a firm's performance, especially its digital innovation performance, is hardly studied. This research uses organizational learning theory to discover if having earlier downsizing experience could enhance a firm's post-employee downsizing digital innovation performance. The results partially support the understanding that having prior employee downsizing experience enhances the firm's post-employee downsizing digital innovation performance. Furthermore, partial support is found in explaining leadership stability's impact on a firm's post-employee downsizing digital innovation performance. However, as the analyses have been performed based on a relatively small sample size, the results should be interpreted cautiously. Furthermore, it is suggested that further research is needed to fully discover the potential that organizational learning theory may have to better understand its usage for understanding a firm's post-employee downsizing performance. Moreover, it is suggested that the context in which the downsizing took place and how the downsizing took place can be of interest for future research.

Keywords: employee downsizing; restructuring; digital M&A; digital innovation performance; organizational learning; prior employee downsizing experience; CEO tenure

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1 Introduction

Digital innovation is characterized by using digital technology in a wide range of innovations (Hinings et al., 2018). The term “digital” refers to the conversion from mainly analog information into the binary language understood by computers. Digital innovation is focused on the creation of or change in market offerings that result from the use of digital technologies (Nambisan et al., 2017). Next to creating new or changing current market offerings, digital innovation can aid firms into creating new processes, new services, new platforms, or even new business models (Nambisan et al., 2017). It thus should come to no surprise that in current industrial developments, digital innovation is acknowledged as a critical capability that a firm needs to possess to maintain its sustainable competitive advantage (Ghobakhloo & Fathi, 2020; Miceli et al., 2021; Pedersen et al., 2018).

For firms to increase their digital innovation they can engage in digital mergers & acquisitions (digital M&A). Digital M&A is defined as a type of consolidation of two firms to obtain knowledge to build intellectual capital and launch innovative solutions (Hanelt et al., 2021). This is often done to create and sell new digital products and services (Hanelt et al., 2021). In the case of digital M&A, the acquirer obtains new resources that can be used to digitally innovate its business model.

However, if a firm performs multiple acquisitions, it risks that its managerial resources become overstretched (Barkema & Schijven, 2008). They become overstretched as, for example, the limited managerial resources are used to ensure effective coordination of the acquiring firm (Barkema & Schijven, 2008). If the acquiring firm is deprived of its available managerial resources, then the firm will have a harder time to integrate new acquisitions (Barkema & Schijven, 2008). To combat less optimal integrations of new acquisitions, downsizing practices are used to free up managerial resources (Barkema & Schijven, 2008).

Furthermore, Krishnan et al. (2007) explain that the creation of synergies is the primary motive for many acquisitions. These synergies are created by combining the complementary resources of both firms. However, when the returns of the newly created synergies are not showing, the management of a firm seeks to go through downsizing activities to streamline operations and to reduce redundancies to utilize its synergies (Krishnan et al., 2007).

Additionally, with the focus on digital innovation, firms show a shift in the skills needed among their employees. With the increasing use of automation and artificial intelligence, demand

for skills related to physical, manual, and basic cognitive tasks is decreasing, while demand is increasing for skills that are focused on higher cognitive, social and emotional, and technological tasks (Bughin et al., 2018). This results in that firms need to hire individuals who have the required skills and that they release employees that do not fit the required skills (Bughin et al., 2018). This thus also plays a role in why firms opt for employee downsizing.

In recent years, focus has been brought upon other areas that seem to be impacted by downsizing activities other than purely a firm's financial performance (Datta et al., 2010). Some examples of this are the impact of downsizing on employee performance (Cornea et al., 2021; Marques et al., 2014; Saïd et al., 2007), Corporate Social Responsibility perceptions (Bergström & Diedrich, 2011; Lakshman et al., 2014), and innovation (Bommer & Jalajas, 1999; Gandolfi & Oster, 2010; Marques et al., 2014).

In the case of (digital) innovation, employee downsizing has been found to negatively impact the remaining employee's morale, enthusiasm for innovation, and workload (Mellahi & Wilkinson, 2008). Next to that, Mishra et al. (2009) found that employee downsizing negatively impacted employees' trust and empowerment, which resulted in lower firm innovativeness. Thus, showing that employee downsizing can harm digital innovation performance.

It thus seems counterintuitive to perform employee downsizing as it decreases digital innovation, and as digital innovation is seen as an important capability for a firm's survivability. However, most often, firms opt for employee downsizing if the firm is lacking in (financial) performance (Cascio et al., 2021). So, they may not have a real choice between if they would or would not downsize. This is also reflected in practice as, for example, at the start of the corona crisis, unemployment surged from 4.4% in March 2020 to 14.8% in April 2020 in the United States alone (Falk et al., 2021). This surge was mostly caused by the increase in layoffs due to the economic recession (Falk et al., 2021).

Nevertheless, in literature there is a gap in explaining how organizational learning influences post-downsizing firm performance (Bergh & Lim, 2008). The role of having earlier experience has been shown to positively impact a firm's performance in the context of firm growth via, for example, M&A (Bhussar et al., 2022; Du et al., 2021). As it has been shown that earlier experience in M&A increases a firm's post-M&A performance (Bhussar et al., 2022; Du et al., 2021). It would be expected that the opposite is also true. Thus, firms with prior experience in employee downsizing show an increase in their post-employee downsizing digital innovative

performance. This would be the case as they would have obtained experience that can help them to make better downsizing decisions, which would result in fewer negative consequences.

Furthermore, the role of how long the leader of the firm has been in charge has also found to be of importance to a firm's innovative performance (Chen, 2013). This is the case as CEO tenure has shown to play a key role in how a firm organizes its resources and capabilities to enhance innovation performance (Wu et al., 2005). CEO tenure relates to organizational learning as it is of influence on how organizational learning routines are established within the firm, and as a CEO's build-up experience throughout their tenure impacts their attitude to partake in initiatives to increase the firm's innovation performance (March, 1991; Miller, 1993; Zhang & Rajagopalan, 2004).

To address the gap of the influence of earlier employee downsizing on a firm's post-employee downsizing digital innovative performance and what role leadership stability plays in this, the concept of organizational learning theory is used. Organizational learning is an important concept to explain how firms can acquire knowledge and utilize it. Levitt and March (1988) explain that there are two main ways to acquire knowledge, namely by learning from direct experience and by learning from the experience of others. Managers of a firm can use knowledge to make fewer mistakes, to further develop specialized and standardized routines, and to make more effective implementations (Ahuja & Katila, 2001). The benefits of this have also been shown, as Jimenez-Jimenez and Sanz-Valle (2011) found evidence that organizational learning increased both the firm's performance and its innovation performance.

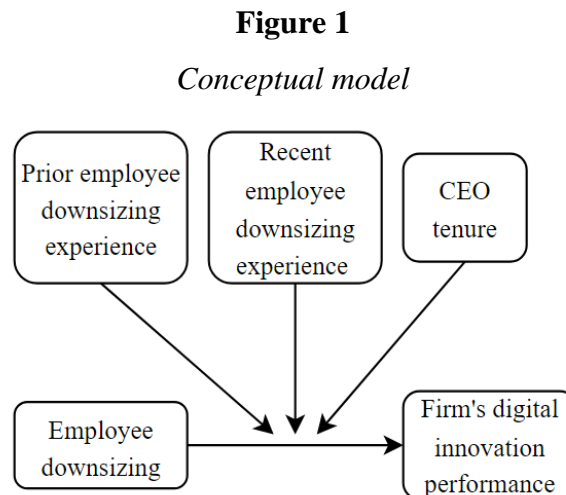
Therefore, it would be interesting to discover if prior employee downsizing experience and leadership stability influences the relationship between employee downsizing and a firm's digital innovation performance. As it can be the case that firms who have prior knowledge about employee downsizing are better capable of combating the negative effects caused by employee downsizing on their digital innovativeness. Understanding this can help firms better compete in the current industrial development in which digital innovation is a crucial capability.

This paper thus aims to examine the role of organizational learning in the relationship between employee downsizing and a firm's digital innovation performance. Using organizational learning theory as a theoretical lens, this paper intends to answer the following research question: *"In which way can organizational learning impact the relationship of employee downsizing on a firm's digital innovation performance?"*.

To answer this question, the following themes will be discussed:

- The use of M&A to increase a firm's digital innovation performance.
- The impact of employee downsizing on a firm's digital innovation performance.
- The role organizational learning (past and recent experience) plays in the relationship between employee downsizing and a firm's digital innovation performance.
- The role leadership stability (CEO tenure) plays in the relationship between employee downsizing and a firm's digital innovation performance.

A conceptual model is created by combining the research question with the relevant themes. This conceptual model can be seen in Figure 1.



2 Literature Review and Hypotheses Formulation

2.1 Use of Mergers and Acquisitions to Increase a Firm's Digital Innovative Performance

Innovation is essential to improve the sustainable competitive advantage of contemporary firms (Petkovska, 2015; Rajapathirana & Hui, 2018; Rosenbusch et al., 2011). This is additionally confirmed by the change in the current industry requirements, as new conditions force incumbent firms to be more innovative to survive and maintain their market share (Ghobakhloo & Fathi, 2020; Miceli et al., 2021; Pedersen et al., 2018). A firm can ensure its safety by utilizing innovation, as this enables them to increase its production, market, and financial performance (Gunday et al., 2011).

To develop a firm's digital innovativeness, digital innovative capabilities are required to have. A firm can acquire capabilities in several ways (Cefis et al., 2020; Kim et al., 2012). Two main

ways to do so are by either developing the required capabilities within the firm itself or by acquiring the necessary capabilities from outside of the organization (Cefis et al., 2020; Kim et al., 2012). To fully acquire external innovative capabilities a firm can engage in M&A (De Man & Duysters, 2005). De Man and Duysters (2005) provide several explanations for why firms opt for M&A to capture their required innovative capabilities. Among others, it is explained that M&A can raise the overall R&D budget of the firms involved. This can create opportunities for them to reap scaling benefits and enable them to go for larger R&D projects that they otherwise would not be able to do (De Man & Duysters, 2005).

The use of M&A to acquire innovative capabilities to enhance a firm's innovative performance in general is also well described within the literature. Hanelt et al. (2021) explain that firms may engage in M&A to digitally innovate their business models to maintain customer bases and market positions to new digital competitors. Furthermore, Datta and Roumani (2015) emphasize the importance of acquiring a target with an already established innovation knowledge base. As acquiring these targets increases the firm's ability to hasten the pace of generating patents (Datta & Roumani, 2015).

Next to that, Cloudt et al. (2006) demonstrate that to obtain the most out of the knowledge base of the target, the acquirer should target firms that are neither too unrelated nor too similar in their knowledge base as the relationship of relatedness is curvilinear (Cloudt et al., 2006). This is furthermore reflected in research conducted by Paruchuri et al. (2006). Paruchuri et al. (2006) showed that the integration of a too different target might result in negative effects on the acquirer's innovative performance. This is, for example, caused by the target's innovators feeling socially isolated and defensive about their research orientations (Paruchuri et al., 2006). This elaborates on the findings of Cloudt et al. (2006) as targeting a firm with a too different knowledge base can thus, in fact, hurt the acquirer's innovation performance.

Next to the distance between knowledge, physical geographical distance also plays a role in the post-M&A innovative performance of the acquirer. McCarthy and Aalbers (2016) showed that every 1000km between the acquirer and target reduced the number of patent applications a year by 19 of what was forecasted. In contrast, if the acquisitions crossed a national border, the firm improved its patent forecast by 3.15 additional patent applications (McCarthy & Aalbers, 2016). The decrease of patents by geographical distance was most likely caused by the increases of transaction and monitoring costs, while the benefits of soft-information (= information that is

difficult to quantify, such as vision and ideas) were reduced (McCarthy & Aalbers, 2016). The increase of patent applications by cross-border acquisitions showed to be positive, while it was expected to decrease due to differences in language, behaviors, and assumptions between the culture of the acquirer and target (McCarthy & Aalbers, 2016). It thus showed that in technological deals innovation is subjected to distant and cross-border M&A.

In summary, digital innovation is crucial in ensuring a firm's survival in current and developing industrial developments. To acquire the necessary digital innovative capabilities, firms can opt to use M&A strategies. Acquiring digital innovative capabilities can enhance the innovation performance of firms. However, there are factors that can influence the post-M&A innovation performance of a firm, such as the distance between the acquirer and its target in both "knowledge" and "physical" sense.

2.2 Impact of Employee Downsizing on a Firm's Digital Innovative Performance

Within this research, focus will be brought upon one specific kind of downsizing, namely employee downsizing. To provide clarity on how this term is used within this research, the definition provided by Datta et al. (2010), based on their meta-analysis of employee downsizing literature, is used. Datta et al. (2010) define employee downsizing as "*a planned set of organizational policies and practices aimed at workforce reduction with the goal of improving firm performance.*". The key takeaway of this definition is that employee downsizing is viewed as an intentional strategic event that involves the undertaking of organizational policies and actions to reduce its number of employees in order to improve firm performance (Datta et al., 2010).

Within the literature, there are several clear answers to why firms engage in downsizing. Cascio et al. (2021) explain six overarching motives of firms to do so. These six motives are (1) company performance, (2) managerial foresight, (3) economy, (4) political risk, (5) industry competition, and (6) technology (Cascio et al., 2021). These overarching motives return firmly within the literature. Lin et al. (2008) argue that the changing business environment, poor operational performance and stock returns, firm performance, economic recession, and corporate disciplinary events are significant drivers of operational restructuring. Renneboog and Szilagyi (2008) explain that restructuring activities are broadly motivated by either poor performance, strategic opportunities, or to correct valuation errors. The importance of (financial) performance is however undoubtedly one of the main drivers of downsizing as it is found to be a reoccurring

theme within literature (Cascio et al., 2021; Datta et al., 2010; Johnson, 1996; Li et al., 2019; Powell & Yawson, 2007).

It thus should come as no surprise that even after a firm engages in digital M&A to increase its digital innovation performance, it can still undergo employee downsizing activities when it is lacking in performance. There are several reasons why firms may engage in M&A in general in the first place. Some examples are to obtain experienced employees, to gain scarce resources, to enter new markets, to obtain a mature operational and administrative system, to reduce business risk, and to achieve synergies (Calipha et al., 2010; Candra et al., 2021; Krishnan et al., 2007). Its overarching goal is to grow the firm and strengthen its sustainable competitive advantage (Candra et al., 2021; Krishnan et al., 2007). However, when the advantages of M&A are not showing, and the firm lacks performance, its management might opt for downsizing to improve its performance (Krishnan et al., 2007). Furthermore, a firm might downsize when it lacks the means to support the acquired resources (Barkema & Schijven, 2008). In order to make sure that the firm's performance is not hindered by an overload of activities that require resources, it might seek out downsizing to slim down (Barkema & Schijven, 2008).

Considering digital M&A, it can also be the case that the skills of the current employees working at the firm do no longer fit the required skills needed in the firm's digital transformation. As explained earlier, by performing a digital M&A the firm obtains new resources that can be used to digitally innovate its business model (Hanelt et al., 2021). This digital transformation is reflected in that an entity, such as a machine, is significantly changed in its properties through the combination of information, computing, communication, and connectivity technologies (Vial, 2019). Examples of such disruptive digital transformations are the adoption of automation and artificial intelligence technologies (Bughin et al., 2018). Bughin et al. (2018) explain that it is expected that the implementation of these new technologies will create a shift in the workforce of a firm. This will be reflected in that firms will hire people who have the required skills to work with these new technologies and that firms will release employees that do not possess or cannot be trained to acquire the required skills (Bughin et al., 2018). However, limited knowledge is available to consider the full impact of digital transformation. Research by Krutova et al. (2021) has shown that production automation can result in an increase in job loss and unemployment. However, the complexity of the labor also plays a role in this, as it is easier for automation to carry out "simple" tasks rather than "complex" tasks (Krutova et al., 2021). Thus, providing the assumption that

automation is more likely to replace simple labor and putting these employees' employment status at risk.

However, performing employee downsizing is found to influence a firm's innovation performance and can thus also impact its digital innovativeness. Bommer and Jalajas (1999) discovered in their study that employee downsizing often yielded some short-term benefits for the firm, but the firm's ability to innovate new products and processes is compromised over the long term. Furthermore, it is found that employee downsizing creates obstacles that hinder a firm's innovativeness, such as a negative influence on the employee's morale, reduced enthusiasm for innovation, and increased workloads (Mellahi & Wilkinson, 2008). Next to that, Mishra et al. (2009) found that employee downsizing negatively impacted employees' trust and empowerment, which resulted in lower firm innovativeness. Furthermore, Aalbers et al. (2014) explain that networks have an essential role in transferring innovative knowledge within an organization. An exogenous network shock, such as employee downsizing, results in a sudden tie loss of an employee's network. Depending on the initial structural embeddedness of an employee, it can be hard for them to establish new ties in their network (Aalbers, 2020). Employee downsizing can thus result in a (temporarily) disruption in the innovative knowledge transfer within a firm, as the employees need to deal with establishing new ties for exchanging innovative knowledge as their existing ones may have disappeared due to the downsizing.

The scale of the downsizing is a relevant factor that influences the post-downsizing performance of the firm (Brauer & Laamanen, 2014; Munoz-Bullon & Sanchez-Bueno, 2010). By performing small-scaled employee downsizing, the firm eliminates inefficiencies in its operations while maintaining the same routines as before (Brauer & Laamanen, 2014). By not changing operational routines in combination with reducing inefficiencies, firms are able to increase their profitability as they show improved operational efficiency (Brauer & Laamanen, 2014). However, there is a difference between medium and large-scaled employee downsizing. In the case of large-scaled employee downsizes, the firm also reduces inefficiencies. However, as the routines are radically changed by the disruptions within the firm caused by the downsizing, the firm is forced to create new routines to replace the old ones (Brauer & Laamanen, 2014). By doing so, the firm is able to increase its profitability (Brauer & Laamanen, 2014). In contrast to small and large-scaled employee downsizing, medium-scaled employee downsizing shows a different result. While medium-scaled employee downsizing also impacts the routines as large-scaled employee

downsizing does. The impact of the disruptions of the change in routines is not as significant as it is for large-scaled employee downsizing. This causes that the firm does not feel forced enough to adapt or redesign organizational routines in order to support current operations (Brauer & Laamanen, 2014). Subsequently, the firm's routines are less developed and will lead to a negative impact on a firm's innovation performance as the routines are suffering of inefficiency.

Based on the above information, it could be reasoned that employee downsizing leads to a negative impact on a firm's innovation performance (Bommer & Jalajas, 1999; Mellahi & Wilkinson, 2008; Mishra et al., 2009). This would be the case as employee downsizing causes negative effects of the survivors of the downsizing within the firm, such as reduced enthusiasm for innovation and a disruption in their innovative knowledge network (Aalbers et al., 2014; Mellahi & Wilkinson, 2008). It is expected that the scale of employee downsizing plays a role in the post-employee downsizing firm's digital innovation performance (Brauer & Laamanen, 2014; Munoz-Bullon & Sanchez-Bueno, 2010). Especially, it is expected that medium-scaled employee downsizings are impactful enough to alter the current operational routines, but that this alteration of the routines is not big enough to meet its requirements, which causes a firm to operate inefficiently. At the same time, medium-scaled employee downsizings are not large enough to force a firm to structurally change its routines to meet the new requirements. This also causes medium-scaled employee downsizings to lead to poorer firm performance than small and large-scaled employee downsizings would do (Brauer & Laamanen, 2014). Grounded in this reasoning, the following hypothesis is created:

Hypothesis 1: *The firm's digital innovation performance will decrease in relation to the scale of employee downsizing within the firm, with it being a U-shaped pattern.*

2.3 The Role of Organizational Learning in Employee Downsizing

This research uses organizational learning theory as a base for its theoretical lens. Organizational learning is a broad concept, as organizational learning is defined as a change in the organization's knowledge that occurs as a function of experience (Argote, 2011). Within a firm, organizational learning can be created following a three-step process: creating knowledge from experience, retaining knowledge over time, and transferring knowledge within and between different units (Argote, 2011). Organizational learning is extremely critical for firms as it helps

them be adaptive and responsive to changes in the environment and plays a vital role in fostering innovation (Dasgupta & Gupta, 2009).

However, little research has been done to discover what role this concept plays in the relationship between downsizing and firm performance in general. Past research primarily focused on the influence of experience on a firm's performance considering growth strategies, such as M&A and alliances (Bergh & Lim, 2008). Recent examples of this are Bhussar et al. (2022), who expanded on the effect of repetitive acquisitions on firm innovation, Du et al. (2021), who researched the impact of prior acquisition experience on firm performance after cross-border acquisitions, and Cho and Arthurs (2018), who examined the influence of acquirers' alliance experience on acquisition outcomes. According to Brauer et al. (2017), Bergh and Lim (2008) were the first to provide empirical evidence that a firm's divestiture experience leads to improved financial performance. To examine this relationship, the concepts of absorptive capacity and organizational improvisation of organizational learning theory were used (Bergh & Lim, 2008).

This research will elaborate on these concepts to examine their effect on the relationship between employee downsizing and a firm's digital innovative performance. Absorptive capacity is found to be prominent in organizational problem solving and is developed through stockpiling experiences (Huber, 1991; Levitt & March, 1988). Absorptive capacity is seen as a firm's memory in which new experiences create knowledge that can be used to improve decision making, update knowledge stocks, and to overcome traps in knowledge development (Lane et al., 2006; Zahra & George, 2002). Absorptive capacity refers thus to the knowledge that a firm has developed through the accumulation of total experience. Organizational improvisation differs from absorptive capacity, as this concept focuses on how learning can occur in short-term, recent, and real-time settings (Brown & Eisenhardt, 1995; Vera & Crossan, 2005). In these settings, a firm must perform an action that occurs without advanced planning or long-term experience (Crossan et al., 2005; Eisenhardt & Tabrizi, 1995). To do so, organizational improvisation focuses on recent experiences that managers use to make decisions (Eisenhardt & Tabrizi, 1995).

Next to the concepts of absorptive capacity and organizational improvisation, this research also focuses on the concept of leadership stability. Within organizational learning, the notion of stability is reflected. By having stability within the organization, an organization can create routines to foster learning (March, 1991). The stability of leadership is of importance to this, as unstable leadership causes ambiguous goals and creates conflict due to the unalignment of different groups

within the organization to these goals (March, 1991). Furthermore, a change in leadership by CEO succession has been associated with changes in structures and processes within the organization (Miller, 1993). In relation to this, changes in goals of the required knowledge that needs to be developed result in necessary changes in established learning processes (Levinthal & March, 1993).

2.3.1 The Role of Total Past Experience

A firm can increase its absorptive capacity by having earlier experience with corporate restructuring (Hayward, 2002; Zollo & Singh, 2004). By expanding this knowledge pool, a basis is founded that the management of a firm can utilize to make fewer mistakes, further develop specialized and standardized routines, and make more effective implementations (Ahuja & Katila, 2001). Furthermore, it has been discovered that firms with higher levels of experience are better at refining, extending, and leveraging existing competencies or creating new ones by utilizing acquired and transformed knowledge in their operations (Zahra & George, 2002).

In the case of corporate restructuring activities focused on M&A, it has been shown that this is the case. Hitt et al. (1998) argued that prior acquisition experience might facilitate identifying and integrating the acquired firm's resources and capabilities. It has shown that this indeed is the case and that this can enhance a firm's post-M&A performance (Du et al., 2021).

Bergh and Lim (2008) hypothesized and found empirical evidence that past corporate restructuring focused on downsizing, especially selloffs and spin-offs, would show similar trends in a firm's past corporate restructuring performance. Brauer et al. (2017) build further on the research by Bergh and Lim (2008) and confirm the hypothesis that corporate restructuring experience positively influences the relationship between corporate restructuring and firm performance. Brauer et al. (2017) focused on the influences of different forms of internal and external corporate restructuring experience on the corporate restructuring and firm performance relationship. Among other things, Brauer et al. (2017) found empiric evidence that the involvement of external restructuring advisors positively moderated the relationship between the number of corporate restructuring in a given year and subsequent firm performance.

Based on this information, it is reasoned that past corporate restructuring experience will also play a role in employee downsizing as it has done for selloffs, spin-offs, and acquisitions (Bergh & Lim, 2008; Brauer et al., 2017; Du et al., 2021). In the case of employee downsizing, it is expected that firms with more experience in this will perform better at employee downsizing than firms with little to no employee downsizing experience. This is expected as it would be likely

that firms with more employee downsizing experience will have built up knowledge that the firm's managers can use to make more effective decisions (Ahuja & Katila, 2001). By making more effective decisions, it is assumed that a firm is more knowledgeable about what it can do to prevent negative outcomes on its post-employee downsizing digital innovation performance. Thus, the second hypothesis in the research is as follows:

Hypothesis 2: *Firms with more experience with employee downsizing will have less negative impact on their post-employee downsizing digital innovation performance after employee downsizing than firms with no to less experience with employee downsizing.*

2.3.2 The Role of Recent Experience

Concerning organizational improvisation, it is found that managers are better able to apply learning from recent experiences to decisions in which improvisation is needed (Eisenhardt & Tabrizi, 1995). However, the more distant experience is, the more likely it is that this experience is less applicable to the new focal restructuring event. This is the case as the new restructuring event might not be related to the individual nature and problems of the past restructuring experience (Bergh & Lim, 2008).

This is also reflected in the research conducted by Bergh and Lim (2008). Their research found empirical evidence that recent corporate restructuring (three to four years prior to the focal restructuring event) was related more positively to financial performance after a restructuring event than firms that did not have recent corporate restructuring experience.

Based on this information, it is reasoned that recent experience with employee downsizing would be more beneficial to a post-downsizing firm's digital innovative performance than it would be for a distant employee downsizing experience. This would be the case as recent employee downsizing experience would be more similar to the focal employee downsizing activity (Bergh & Lim, 2008). Furthermore, it is expected that employee downsizings take place infrequently. Therefore, managers would be able to make better improvisational decisions when the experience is more recent (Eisenhardt & Tabrizi, 1995). Based on this information, the third hypothesis of the research is formulated:

Hypothesis 3: *Recent experience with employee downsizing will lessen the negative effect of employee downsizing on a firm's digital innovation performance more than distant experience with employee downsizing.*

2.3.3 *The Role of Leadership Stability*

The term leadership stability can be defined as how long the same person remains in charge within a firm (Zhu & Zhang, 2017). In the case of a firm, most often the CEO is the person in charge of the firm and of whom it is expected to express leadership (Farkas Charles & Suzy, 1998). To refer to this stability, the term CEO tenure is used. The critical role of CEO tenure has been reflected in literature when focused on a firm's performance and a firm's innovative performance (Allgood & Farrell, 2000; Chen, 2013; Luo et al., 2014; Musteen et al., 2010; Simsek, 2007).

Referring to the impact of CEO tenure on a firm's performance, it is found that it can have both a negative and positive effect on firm performance (Miller & Shamsie, 2001). In the early phase of a CEO's tenure, the firm performs relatively better (Luo et al., 2014; Wu et al., 2005). This is the case as CEOs tend to learn rapidly and are willing to take risks (Wu et al., 2005). However, in the later phase of a CEO's tenure, CEOs tend to commit to obsolete paradigms, become risk-averse and tend to adapt less to the external environment (Levinthal & March, 1993; Miller, 1991). This results in lower firm performance later in a CEO's tenure.

Similar results are found in the case of innovation, as an inverted U-shaped relationship is discovered between CEO tenure and innovation (Chen, 2013). Literature shows that CEO tenure plays a key role in organizing a firm's resources and capabilities to enhance innovation performance (Wu et al., 2005). Due to the high variability of outcomes and a high chance of failure, innovation is seen as inherently risky (Balkin et al., 2000). It has been discovered that in the early and late phases of a CEO's tenure, CEOs are more likely hesitant to pursue risky innovation strategies due to several reasons (Simsek, 2007; Souder et al., 2012; Wu et al., 2005). For example, as CEOs have a relative lack of experience and knowledge about the firm and its industries in the early phase of its tenure (Wu et al., 2005). Furthermore, in the late phase of a CEO's tenure, CEOs tend to avoid risky activities due to a relatively limited knowledge base resulting from their complacent with prior success and belief in possessing sufficient experience and knowledge (Hambrick & Fukutomi, 1991; McClelland et al., 2010). In the middle phase of a CEO's tenure, CEOs tend to be more risk-taking as they have accumulated more experience and become more familiar with the firm (Herrmann & Datta, 2006; Jaw & Lin, 2009).

In the case of organizational learning, the need for stable leadership within a firm is also reflected. Changing the CEO of a firm can lead to alterations in the knowledge, skills, and interaction processes at the top of the company (Virany et al., 1992; Zhang & Rajagopalan, 2004).

Furthermore, by having stability within the leadership, a firm can set clear goals and ensure all employees are well aligned to these goals (March, 1991). Next to that, changes in CEO tend to disrupt current structures, routines, and processes with the firm (Miller, 1993). This implies that established learning processes may be temporarily disrupted as they might need to be changed to comply with the new goals set by the new CEO (March, 1991).

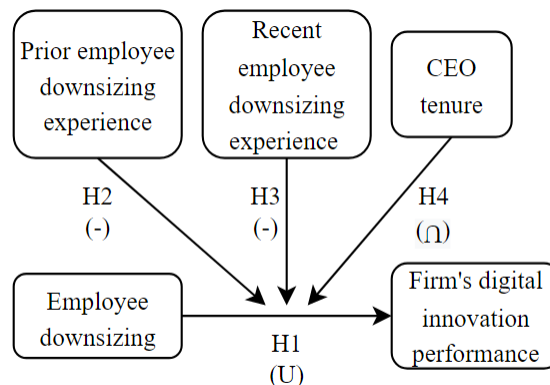
Based on this information, it is reasoned that CEO tenure would show an inverted U-shaped relationship with a firm's digital innovation performance. This would be the case as CEOs tend to be less risk-taking in their tenure's early and late phases (Luo et al., 2014; Miller, 1991; Wu et al., 2005). While performing risky activities is necessary to improve a firm's innovation (Balkin et al., 2000). In addition, it is expected that established organizational learning processes are temporarily suboptimal in the early phase of a CEO's tenure as the firm needs to adjust to new leadership (Virany et al., 1992; Zhang & Rajagopalan, 2004). Based on this reasoning, the fourth and final hypothesis is formulated:

Hypothesis 4: *The relationship between employee downsizing and a firm's digital innovation performance will be impacted by CEO tenure, as CEO tenure will impact this relationship to be an inverted U-shaped pattern.*

To summarize, based on this literature review, the conceptual model, as earlier shown in the introduction, has been modified to incorporate the created hypotheses. The complete conceptual model can be found in Figure 2.

Figure 2

Full conceptual model



3 Methods

3.1 Sampling Methods

This research focuses on the effect that employee downsizing experience has on the relationship between employee downsizing and the firm's digital innovation performance. To explore this, the context of digital M&A is used. Namely, firms that performed digital M&A prior to their focal employee downsizing activity. This is done for two reasons. First, it shows that the firm is consciously trying to improve its digital innovation. Thus, making it easier to specify observations for the sample. Second, as Barkema and Schijven (2008) noted, firms that perform M&A activities are more likely to go through downsizing activities to unlock synergies in the long run. This provides a higher chance that firms engaging in digital M&A to increase their digital innovativeness are likely to take part in employee downsizing activities as well, which is of interest in this research.

The hypotheses stated within this research were tested by using a sample of firms that performed employee downsizing after exercising digital M&A and are engaged in digital innovation. An already established dataset created by PhD candidate X has been used as a foundation of the sample of this research. The focus of the sample is on M&A deals performed during the period of January 01, 2000, to January 01, 2017. This dataset contained a sample size of 3289 observations.

After the initial sample of firms that performed M&A was created, the sample was refined by determining if the acquirer performed employee downsizing activities after performing M&A. To conclude if a firm exercised employee downsizing, the approach of Cascio et al. (2021) was used, in which downsizing is defined as employee downsizing if the decline of employees is greater than 5%, but the reduction in plant and equipment is less than 5%. However, to consider that even small percentages of employee downsizing can imply a layoff of hundreds of people, a cutoff point of 3% was used instead of 5% (Brauer & Laamanen, 2014; Tangpong et al., 2015). Firms that did not perform employee downsizing after exercising a M&A were removed from the sample. This reduced the sample size from 3289 to 620 observations.

Lastly, based on the works of Hanelt et al. (2021), for an M&A deal to remain within the sample, the deal's descriptions were analyzed by four independent researchers to look for keywords indicating that the target leveraged digital technologies as critical elements of their business models. The observations that were deemed not fit (three or more noes to the question if the M&A

was considered digital), were removed from the sample. This further reduced the sample size from 620 to 530 observations.

3.2 Dependent Variable

Within this research, the focus is brought upon the post-employee downsizing digital innovation performance of a firm. In short, this dependent variable is called *Digital innovation*. Within literature, it was found that a firm's innovation performance is often measured by the number of patent applications filed (Clodt et al., 2006; Datta & Roumani, 2015; Kim et al., 2012; Sun, 2014). To distinguish digital patents from regular patents, digital patents are only seen as digital patents if they intensely leverage digital technologies (Hanelt et al., 2021). Following Bielig (2022), patents are defined as digital when they are classified in the digital technology field in the WIPO classifications. These classifications are 4 - Digital communication, 6 - Computer technology, or 7 - IT methods for management. The database of Orbis Intellectual Property was used to obtain the necessary digital patent applications filed data. *Digital innovation* is measured by dividing the total number of patent applications filed two years after employee downsizing took place by the total number of patent applications filed a year prior to the downsizing¹. This discrepancy calculates the change in a firm's digital innovation performance (King 2020; Hanelt et al., 2021).

3.3 Independent Variable

Scale of employee downsizing is used as the independent variable within this research. The variable was measured by calculating the percentual difference of the number of employees remaining one year after employee downsizing in comparison to the number of employees a year prior to the downsizing. The same method as described in the sampling methods paragraph was used to identify employee downsizing. To obtain the data, the database of Refinitiv/Eikon was used.

3.4 Moderator Variables

Within this study, three moderator variables are used. The first moderator variable is *Number of prior employee downsizing experience*. This variable will consider the total number of employee downsizing experiences a firm had ten years prior to the focal employee downsizing

¹ Three other timeframes were developed as well but will not be fully elaborated upon in the main text of this research. This was done as it can be the case that in the long term a firm's ability to innovate may be compromised by downsizing (Bommer & Jalajas, 1999). The results of these separate timeframes can be found in Appendix A.

activity in the. The earlier described method is used to identify employee downsizing. Following research by Bergh and Lim (2008), a ten-year period is used from the focal downsizing activity as older experiences might not be as applicable anymore to new situations. The necessary data to create this variable is obtained from the Refinitiv/Eikon database. This metric variable will contain the number of employee downsizing activities ten years prior to the focal employee downsizing activity.

Two dummy variables were computed to check whether a firm has recent employee downsizing experience. These are *Not having prior employee downsizing experience* and *Having prior employee downsizing experience*. These dummy variables are made to check if the firm has performed employee downsizing in the ten years prior to the focal employee downsizing activity. For an observation to be included in the prior employee downsizing dummy variable, a discrepancy of at least 3% of the number of employees must be noticed between two years in the prior ten years period, while the decline in property, plant and equipment must be lower than that. To obtain the necessary data to create the two dummy variables, the database of Refinitiv/Eikon was used.

CEO tenure is used as the third moderator variable. This variable will reflect how stable the leadership has been within the firm at the time of downsizing. Following Luo et al. (2014), CEO tenure is measured as the number of years of CEO experience in the position. To obtain the necessary data, the database of BoardEx was used. Furthermore, to reduce missing values, individual firms were manually looked up online to check for publicly available data on their CEO's tenure at the time of the focal employee downsizing activity.

3.5 Control Variables

In this research, several control variables are established to explain the possible influences of employee downsizing on digital innovation performance. In line with prior research on innovation performance, *R&D expenditure* (hereafter called *Firm R&D*) and *Firm size* are added as control variables (Pesch et al., 2021). *Firm R&D* is measured as the share of R&D expenditures relative to total sales (Pesch et al., 2021). This variable will consider the R&D expenditures a year before the focal employee downsizing activity. *Firm size* is used to check whether the firm's size is of impact on the hypothesized relationships. This control variable is measured by the total number of employees at the end of the year preceding the focal employee downsizing activity (Luo et al., 2014; Saïd et al., 2007).

Next, return on assets (*Firm ROA*) indicates a firm's performance when the downsizing occurred. This is measured by the return on assets of a firm a year prior to the focal employee downsizing activity taking place (Barkema & Schijven, 2008; Bergh & Lim, 2008; Wang & Bai, 2021). In addition, *Time between digital M&A and employee downsizing* is used to discover if different timings of employee downsizing by firms are of impact on the hypothesized relationships. This measurement will be of metric scale in which the total years between digital M&A and the focal employee downsizing activity are counted. Furthermore, *Firm age* is used as a control variable to consider the firm's age at the time of employee downsizing. As it can be the case that older firms have developed routines to support product innovation (Pesch et al., 2021). This will be measured as the number of years since the establishment of the company in comparison to the year in which the employee downsizing took place (Pesch et al., 2021).

The Refinitiv/Eikon database was used to gather data for *Firm R&D*, *Firm size* and to check when the focal employee downsizing activity took place after the firms exercised digital M&A. The dataset provided by PhD candidate X contained the years in which the firms exercised a digital M&A, so no databases were used for this. The database of Orbis was used to obtain data when the firms were incorporated to check the firms' age at the year of the focal employee downsizing activity.

3.6 Research Ethics

The research was conducted with the principles of the Netherlands Code of Conduct for Research Integrity in mind. Radboud University Nijmegen also endorses this code. By following this code of conduct, the researcher follows the following principles: (1) honesty, (2) scrupulousness, (3) transparency, (4) independence, and (5) responsibility (KNAW et al., 2018). This implies that the researcher will ensure that no fabrication, manipulation, plagiarism, misrepresentation, mismanagement or inadequate preservation of material, breach of duty of care, and abuse of status is used in executing the research. Furthermore, it is disclosed that this research builds upon an already established dataset provided by PhD candidate X. Next to that, as this research uses public quantitative data, it does not foresee violating the privacy of firms that have been included in the sample. To ensure privacy, no individual firm-level conclusions will be made based on the findings (e.g., naming a firm by name).

4 Analyses and Results

4.1 Analyses Approach

Linear regression (ordinary least squares) has been used as the primary method to conduct the analyses to discover the relationships between the multiple independent variables and the single dependent variable within this research. As it is the case that multiple independent variables are analyzed with a single dependent variable, these analyses will use multiple regression analysis (MRA). In the case of MRA, all variables need to be of metric scale. This requirement is met as the dataset only contains metric and dummy variables. To discover if influential cases were within the analyses, the Cook's Distance statistic was used. If the Cook's Distance is higher than or equal to 1, then it can be concluded that there is at least one influential case that can be considered as an outlier within the analysis (Hair et al., 2020). In the case that the influential case is an ordinary observation in its individual characteristics but exceptional in its combination of characteristics, then the case should be retained in the sample (Hair et al., 2020). Robust regression was used to consider their impact when a Cook's Distance of 1 or higher was observed. To interpret the model, the robust regression coefficients were used in which one-tailed t-values were used to test the significance of the independent variables and the interaction effects, and the two-tailed t-values were used to test the significance of the control variables. Furthermore, if the model showed heteroscedasticity (if the modified Breusch-Pagan test showed to be significant), then an additional analysis was made based on the robust standard errors with the HC3 method to interpret the regression coefficients results.

4.2 Descriptive Statistics

4.2.1 Missing Values

A missing value analysis was performed along with Little's MCAR test to check the original dataset on missing values. Table 1 shows the results of this analysis.

Table 1

Missing value analysis

Variable name	<i>N</i>	Missing percent
Scale of employee downsizing	109	0
Number of prior employee downsizing experience	109	0
Not having prior employee downsizing experience	109	0
Having prior employee downsizing experience	109	0
CEO tenure	75	32.2
Digital innovation (a year prior to the year of employee downsizing)	109	0
Digital innovation (a year prior to one year after employee downsizing)	90	17.4
Digital innovation (a year prior to two years after employee downsizing)	80	26.6
Digital innovation (a year prior to three years after employee downsizing)	46	57.8
Firm age	109	0
Firm size	109	0
Firm ROA	99	9.2
Firm R&D	87	20.2
Time between digital M&A and employee downsizing	109	0

Note. Little's MCAR test: Chi-square = 233.525, DF = 192, Sign. = 0.022

The overview shows a high score of missing values for *CEO tenure* (32.2%), *Firm ROA* (9.2%), and *Firm R&D* (20.2%). *Digital innovation* shows missing values as well (17.4 to 57.8%). However, as the original dataset will be split into different timeframes, no action will be taken to reduce its missing values. The main text of this research will focus on the timeframe of a year prior to employee downsizing to two years after employee downsizing. The results of the analyses for the other timeframes can be found in Appendix A. Little's MCAR test shows that the missing values are MAR ($p = .022$). Therefore, the Expectation Maximization (EM) imputation method was used to replace missing values. EM imputation is a sound method to use in both MCAR and MAR situations and is especially useful when the missing values are over 20% (Hair et al., 2020).

4.2.2 Skewness and Kurtosis

To combat skewness and kurtosis, any outliers were first removed by deleting scores that had Z-values higher than |3.2|. After deleting the outliers, any still problematic variables were transformed. In preparation for the regression analyses, *Scale of employee downsizing*, *Number of*

prior employee downsizing experience, and *CEO tenure* were centered. To consider the possible curvilinear effect of *Scale of employee downsizing* and *CEO tenure*, the variables were quadrated after centering. An overview of the variables and their correlations can be found in Table 2.

Table 2

Descriptive statistics

#	Variable	<i>M</i>	<i>Std. Dev</i>	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1	Firm age	63.64	50.56	5	202	1										
2	Firm size	8.50	1.20	6.14	10.98	0.32	1									
3	Firm ROA	3.80	6.60	-13.85	25.05	0.30	0.26	1								
4	Firm R&D	368.06	148.16	1	881.64	0.32	0.59	0.15	1							
5	Time between digital M&A and employee downsizing	3.40	1.95	1	10	0.35	0.06	0.11	-0.19	1						
6	Not having earlier employee downsizing experience	0.34	0.48	0	1	0.22	0.11	0.24	0.04	0.36	1					
7	Having earlier employee downsizing experience	0.66	0.48	0	1	-0.22	-0.11	-0.24	-0.04	-0.36	-1	1				
8	Number of prior employee downsizing experience	0.00	1.28	-1.28	3.72	-0.2	-0.09	-0.30	-0.05	-0.35	-0.73	0.73	1			
9	Scale of employee downsizing	0.00	0.01	0.00	0.05	-0.02	-0.02	0.06	-0.02	0.02	-0.04	0.04	-0.01	1		
10	CEO tenure	18.06	38.77	0.00	248.53	0.04	-0.07	0.00	-0.07	-0.01	-0.01	0.01	0.26	-0.10	1	
11	Digital innovation	-0.06	0.69	-0.95	1.80	-0.24	-0.29	-0.28	-0.31	-0.09	-0.12	0.12	0.07	0.14	-0.14	1

Note. $N = 58$.

Regarding the correlations, it is noted that correlation has been found between some of the variables. According to Hair et al. (2020) correlations above 0.70 should be taken seriously. Within the datasets, it is noticed that *Number of prior downsizing experience* correlates with the variables *Having earlier downsizing experience* and *Not having earlier downsizing experience* (-0.73 and 0.73, respectively). Reflecting on this, it seems to make sense, as when a firm exercised employee downsizing before, the observation should both count to the *Having earlier downsizing experience* and the *Number of previous downsizing experience* variables. Furthermore, the dummy variables *Having earlier downsizing experience* and *Not having earlier downsizing experience* correlate strongly with each other (-1). This is of course the case as they are the complete opposites of each other. Within the analyses, the dummy variable *Having earlier downsizing experience* was taken as reference variable.

Furthermore, it became clear that the sample size was relatively small ($N = 58$). According to Hair et al. (2020), in the case of MRA, the sample size should be at least 5 observations per variable, but preferable, 15 to 20 per variable. The variables used per model differ in the range of

6 to 13 (including controls and interaction effects). This means that the sample size is on the low side, and the results should thus be interpreted with caution.

4.2.3 *Multicollinearity*

To perform the MRA, it is ideal that the independent variables highly correlate with the dependent variable but have little correlation among the other independent variables (Hair et al., 2020). To check for multicollinearity, the collinearity statistics have been checked. For the independent variables to have little correlation, the tolerance value should be at least above 0.10, and the VIF value should be lower than 10 (Hair et al., 2020). When analyzing the tolerance and VIF values, it became clear that there is some correlation between the independent variables. However, the correlations between the independent variables were above the tolerance value of 0.10 and below the VIF value of 10 (see Table 3).

Table 3

Multicollinearity checks based on tolerance and VIF values

#	Variable	<i>Tolerance</i>	<i>VIF</i>
1	Firm age	0.59	1.71
2	Firm size	0.45	2.22
3	Firm ROA	0.74	1.36
4	Firm R&D	0.52	1.92
5	Time between digital M&A and employee downsizing	0.60	1.67
6	Not having prior employee downsizing experience	0.25	3.96
7	Number of prior employee downsizing experience	0.26	3.90
8	Scale of employee downsizing	0.10	9.78
9	CEO tenure	0.64	1.57

4.3 Assumptions of Multiple Linear Regression Analysis

Four assumptions must be checked to conduct the MRA. These assumptions are (Hair et al., 2020): (1) linearity of the phenomenon measured, (2) constant variance of the error terms, (3) normality of the error term distribution, and (4) independence of the error terms.

4.3.1 *Linearity of the Phenomenon Measured*

The first assumption is to check for linearity. To do so, a scatterplot was created based on ZRESID (the standard residuals) and ZPRED (the standardized predicted values). For this assumption to be met, the dots in the scatterplot should not form a clear pattern around the horizontal zero-line. When analyzing the six different scatterplots, it becomes clear that no pattern can be found (see Appendix B). However, when considering the Cook's Distance statistic, it became clear that two models have influential cases that are important to the analyses. These are

models 5 and 6 as they both have Cook's Distance values higher than 1 (10.086 and 6.776, respectively). Therefore, these models are tested with robust regression analysis to account for the influential cases within these models.

4.3.2 *Constant Variance of the Error Terms*

The second assumption is to check for homoscedasticity in the constant range of the error terms of an independent variable (Hair et al., 2020). First, the same scatterplots are analyzed as used above to analyze patterns in the residuals. Within these scatterplots, no patterns must be formed that could indicate heteroscedasticity. Next to examining the scatterplots, each model was tested based on the modified Breusch-Pagan test. By performing this test, it became clear that there were some indications of heteroscedasticity in models 1, 2, 4, and 5 (see Appendix B). To analyze the coefficients of models 1, 2, and 4, the robust standard errors were used with the HC3 method. Model 5 will still be analyzed with the robust regression analysis due to the inclusion of at least one influential case.

4.3.3 *Normality of the Error Term Distribution*

The third assumption is that the error terms are normally distributed. To check this assumption the normal probability plot can be used (P-P plot). For the assumption to be met, the dots will have to lay on or closely around the diagonal line (Hair et al., 2020). In the case of this research all models showed to have the dots closely aligned to the diagonal line. Therefore, this assumption was met (see Appendix B).

4.3.4 *Independence of the Error Terms*

The fourth assumption in MRA is that each predicted value is independent, implying that the predicted value is not related to any other prediction (Hair et al., 2020). To check this assumption, the Durban-Watson statistic is checked. Field (2017) states that the Durban-Watson statistic should be between 1 and 3, preferably as close to 2 as possible. All models showed to have the Durbin-Watson statistic between 1 and 3. Therefore, this assumption has also been met (see Appendix B).

4.4 Results

The results from the regression analyses can be found in Table 4.

Table 4

Results regression analyses of a year prior to downsizing to two years after downsizing

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Controls						
Intercept	0.92 (0.70)	0.85 (0.73)	1.05 (0.76)	1.10 (0.83)	0.52 (0.73)	0.56 (0.82)
Firm age	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Firm size	-0.04 (0.07)	-0.04 (0.08)	-0.05 (0.10)	-0.07 (0.09)	-0.01 (0.10)	-0.05 (0.11)
Firm ROA	-0.02 (0.01)	-0.02 [†] (0.01)	-0.02 (0.02)	-0.02 (0.01)	-0.02 (0.02)	-0.01 (0.2)
Firm R&D	0.00 [†] (0.00)	0.00 [†] (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Time Between digital M&A and employee downsizing	-0.03 (0.06)	-0.04 (0.06)	-0.05 (0.06)	-0.05 (0.06)	-0.01 (0.05)	0.01 (0.06)
Explanatory variables						
Scale of employee downsizing		11.35 (11.28)	9.08 (10.91)	16.05 (10.77)	13.00 (10.61)	48.27 [†] (31.04)
Number of prior employee downsizing experience			-0.06 (0.09)			0.14 (0.14)
Scale of employee downsizing x Number of prior employee downsizing experience			6.91 (13.38)			-52.69 (42.20)
Not having earlier employee downsizing experience				0.12 (0.23)		0.29 (0.37)
Scale of employee downsizing x Not having earlier employee downsizing experience				-25.08 (30.15)		-118.71 [†] (86.60)
CEO tenure					0.00 (0.00)	-0.01* (0.00)
Scale of employee downsizing x CEO tenure					-0.18 (0.55)	4.29** (0.56)
Adjusted R ²	0.09	0.10	0.07	0.07	0.09	0.07
F	2.14 [†]	2.02 [†]	1.53	1.57	1.67	1.34
N	58	58	58	58	58	58

Note. [†] $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Model 1 represents the base model in which only the control variables are included. The model shows that *Firm R&D* has a significant and positive impact on a firm's post-employee downsizing digital innovation performance two years after the focal employee downsizing activity

(*Digital innovation*) (Model 1, $\beta = 0.00$, $p = .055$). No other control variables show to be of significance in Model 1. Furthermore, *Firm R&D* showed to be of significant positive effect on *Digital innovation* ($\beta = 0.00$, $p = .057$) and *Firm ROA* showed to be of significant negative effect on a *Digital innovation* in Model 2 ($\beta = -0.02$, $p = .098$). In Models 2 to 5, each hypothesis is tested separately, and in Model 6 a total model is represented, including all variables and interaction effects.

Model 2 shows that *Scale of employee downsizing* does not have a significant effect on *Digital innovation* ($\beta = 11.35$, $p = .319$). However, when referring to Model 6, it becomes clear that *Scale of employee downsizing* has a significant effect on *Digital innovation* ($\beta = 48.27$, $t(45) = 1.56$, $p = .063$). Model 6 does, however, show that it does not have a significant model fit ($F = 1.34$, $p = .229$). Therefore, the results of Model 6 should be interpreted with caution. This thus indicates that, as the beta coefficient is positive, there is a U-shaped curvilinear relationship between *Scale of downsizing* and *Digital innovation*. However, as this is only the case in the total model (Model 6) and as Model 6 is of nonsignificant model fit, hypothesis 1 is only partially supported.

Model 3 shows that neither *Number of priors downsizing experience* nor its interaction with *Scale of employee downsizing* is of significant effect on *Digital innovation* ($\beta = -0.06$, $p = .507$, $\beta = 6.91$, $p = .608$, respectively). Moreover, they do not show to be of significance in Model 6 as well ($\beta = 0.14$, $t(45) = 0.99$, $p = .164$, $\beta = -52.69$, $t(45) = -1.25$, $p = .109$, respectively). Therefore, no support is found that the number of prior downsizing experiences has a significant positive effect on a firm's post-employee downsizing digital innovation performance. Thus, hypothesis 2 is rejected.

Model 4 shows that neither *Not having earlier downsizing experience* nor its interaction with *Scale of employee downsizing* is of significant effect on *Digital innovation* ($\beta = 0.12$, $p = .629$, $\beta = -25.08$, $p = .388$, respectively). However, when considering the results of Model 6, it becomes visible that the interaction effect of *Not having prior downsizing experience* with *Scale of employee downsizing* is of significant negative effect on *Digital innovation* ($\beta = -118.71$, $t(45) = -1.37$, $p = .089$). Therefore, it can be concluded that there is partial support for hypothesis 3. However, as it is only found to be the case for the interaction effect and only in Model 6, which has a nonsignificant model fit, this result should be interpreted with caution.

Lastly, Model 5 shows that neither *CEO tenure* nor its interaction effect with *Scale of employee downsizing* is of significant effect on *Digital innovation* ($\beta = 0.00$, $t(49) = -0.94$, $p = .177$, $\beta = -0.18$, $t(49) = -0.33$, $p = .372$, respectively). However, when observing Model 6, it becomes clear that there is evidence that both *CEO tenure* as its interaction effect with *Scale of employee downsizing* is of significant effect on *Digital innovation* ($\beta = -0.01$, $t(45) = -2.03$, $p = .024$, $\beta = 4.29$, $t(45) = 7.68$, $p < .001$, respectively). Noting that the beta coefficient of *CEO tenure* is negative, thus indicating an inverted U-shaped curvilinear relationship with *Digital innovation*, supporting evidence is found in favor of hypothesis 4. However, the interaction effect of *CEO tenure* with *Scale of employee downsizing* shows a significant positive relationship. This goes against the hypothesized relationship that the interaction effect would reduce the curvilinear relationship between *Scale of employee downsizing* and *Digital innovation*. Therefore, hypothesis 4 is rejected.

5 Discussion

The impact of employee downsizing on a firm's post-employee downsizing innovation performance has been acknowledged in prior research (Brauer & Laamanen, 2014; Mellahi & Wilkinson, 2008; Mishra et al., 2009). Despite this body of research, the exact impact that earlier downsizing experience can have on a firm's post-downsizing performance is relatively unknown (Bergh & Lim, 2008; Brauer et al., 2017).

This research uses organizational learning theory to discover how earlier downsizing experience and leadership stability influence a firm's post-employee downsizing digital innovation performance. Organizational learning theory argues that firms can learn from previous experiences and that they can use this to enhance their future performance (Levitt & March, 1988). It was hypothesized that the scale of employee downsizing would show a U-shaped curvilinear relationship with post-employee downsizing digital innovation performance, the same as it has been discovered for innovation in general (Bommer & Jalajas, 1999; Brauer & Laamanen, 2014). The results show partial support that this indeed is the case for digital innovation performance as well. This results in that medium-scaled employee downsizing activities are deemed the worse for a firm's digital innovation performance. This provides the understanding that although digital innovation is a relatively newer concept (Kohli & Melville, 2019), it follows the same trajectory concerning downsizing as innovation performance in general.

However, based on organizational learning theory, it was hypothesized that the accumulated prior employee downsizing experience would influence a firm's post-employee downsizing digital innovation (Brauer et al., 2017). However, the findings did not support this understanding within this research as no significant relationship was found.

Despite this, partial support has been found that having prior employee downsizing experience, with no regard to the exact amount, in the past ten years prior to the focal employee downsizing activity positively impacts a firm's post-employee downsizing digital innovation performance. Thereby confirming the understanding that earlier experience can be of benefit to a firm's future performance (Bergh & Lim, 2008; Levitt & March, 1988). This implies that a firm's digital innovation performance after downsizing would thus be higher if the firm experienced an employee downsizing activity in the ten years before the focal employee downsizing activity.

Lastly, the results partially support the understanding that leadership stability on itself has an inverted U-shaped curvilinear relationship with a firm's post-employee downsizing digital innovation performance. This supports both the understanding that CEO tenure is of significance for digital innovation as well as it is for innovation in general, and that it also follows the same trajectory as it does for innovation (Luo et al., 2014; Musteen et al., 2010).

However, the results did not support the understanding that the interaction of CEO tenure with the scale of employee downsizing would harm the firm's post-employee downsizing digital innovation performance. On the contrary, evidence was found that it even increased the firm's post-employee downsizing digital innovation performance.

5.1 Theoretical Implications

This research contributes to the understanding of the impact that organizational learning can have on a firm's post-employee downsizing digital innovation performance in several ways. First, it adds to the understanding that employee downsizing does not per se follow a linear relationship as partial support is found that the scale of downsizing on its own displays a U-shaped curvilinear relationship with a firm's digital innovation performance. This implies that digital innovation thus follows the same pattern as innovation in general and that digital innovation is also impacted by employee downsizing (Bommer & Jalajas, 1999; Brauer & Laamanen, 2014). This thus reflects the understanding that medium-scaled employee downsizing leads to lower post-employee downsizing digital innovation performance within the firm than small and large-scaled employee downsizing would (Brauer & Laamanen, 2014).

Second, the results of this research show conflicting results based on the understanding of organizational learning theory. It was hypothesized that the accumulation of previous employee downsizing activities would be of influence on the post-employee downsizing digital innovation performance (Brauer et al., 2017). However, no evidence within the results was found that could support this hypothesis. Argote et al. (2021) argue that firms may vary in the rate they learn. Therefore, it could be the case that there might be a cap to the extent of how many prior employee downsizing activities are feasible for a firm to learn from (Desai & Madsen, 2019).

Despite this, partial support was found that having prior employee downsizing experience, with no regard to the exact amount, in the preceding ten years to the focal employee downsizing activity has a significant positive effect on the firm's post-employee downsizing digital innovation performance. Thereby supporting evidence is found that recent experience on its own positively impacts a firm's post-employee downsizing digital innovation performance. This thus shows that similar results are found as it has been for post-employee downsizing firm performance in general (Bergh & Lim, 2008).

Third, the results partially support that leadership stability has an inverted U-shaped relationship with a firm's post-employee downsizing digital innovation performance. Therefore, it confirms the current understanding that a firm's digital innovation performance is highest when the CEO is in the midst of their tenure (Luo et al., 2014). It contributes to the already existing knowledge by displaying that this relationship that the same relationship was found as was found for innovation in general (Luo et al., 2014; Musteen et al., 2010). However, it was also hypothesized that this relationship would negatively impact the relationship between the scale of employee downsizing and a firm's post-employee downsizing digital innovation performance, as the two different U-shaped patterns would cross each other. Despite this hypothesis, no evidence was found that could support this. The results even contrary indicated that the interaction effect would have a significant positive impact on the firm's post-employee downsizing digital innovation performance.

5.2 Practical Implications

This research brings forward several practical implications for managers. First, managers should be aware that different scales of downsizing result in different effects on a firm's post-employee downsizing digital innovation performance. Especially, that medium-scaled employee downsizing activities are generally more likely to result in poorer post-employee downsizing

digital innovation performance. Showing that it might be more ideal to perform small or large-scaled employee downsizing activities if the firm is interested in scoring high in their digital innovation performance.

Second, the result shows partial support that having prior employee downsizing experience can enhance the post-employee downsizing digital innovation performance of a firm. Managers should acknowledge this fact, as this implies that earlier experience with employee downsizing should be taken seriously and into consideration when performing new employee downsizing activities.

Lastly, managers should be aware of CEO tenure's impact on its relationship with the firm's post-employee downsizing digital innovation performance. The results indicate that leadership stability shows an inverted U-shaped relationship with post-employee downsizing digital innovation performance. Thereby expressing that a firm's digital innovation performance is the highest when the CEO is in the midst of their tenure. The interaction effect this has with the scale of employee downsizing even further increases the importance of this concept.

5.3 Limitations and Directions for Future Research

This research was conducted with several limitations. First, this research made use of analyses with relatively small sample size. Therefore, the validity of the results is on the lower side and causes that the results can only be generalized with caution. The small sample size came from the limitations of the available data sources. Digital innovation is still relatively a new phenomenon and lacks coherent definitions and measurements (Hanelt et al., 2021). Therefore, the classifications defined by WIPO were used to measure digital innovation via digital patents filed (Bielig, 2022). To gather the digital patent applications filed data, the Orbis Intellectual Property database was used. However, this database only had patents filed between 2013 to 2022. The original sample consisted of firms that performed digital M&A between 2000 and 2017, and as the different time periods of digital innovation performance had to be considered, this resulted in a small sample size. Therefore, it would be advised to look for other databases that contain data on patent applications filed or use other techniques than classifications to obtain the necessary data.

Second, this research did not consider the context in which employee downsizing occurred. Within organizational learning, organizations create knowledge when their organizational experience interacts with the context in which they operate (Argote & Miron-Spektor, 2011). For example, it has been found that organizational learning is promoted in contexts where employees

feel psychologically safe or can trust each other (Edmondson, 1999; Kane et al., 2005). Regarding downsizing, it has been found that there are six primary reasons why firms opt for downsizing (Cascio et al., 2021). With the dominant reasons being firm performance and managerial foresight. Regarding organizational learning and downsizing, it would be interesting to discover how the contexts of organizational learning and downsizing interact with each other and how this would impact a firm's digital innovation performance.

Lastly, this research did not consider how employee downsizing occurred. Employee downsizing often impacts a firm's innovativeness negatively. An explanation of this is that downsizing negatively influences the innovator's morale, trust, empowerment, enthusiasm for innovation, and workload (Mellahi & Wilkinson, 2008; Mishra et al., 2009). Research has indicated that so-called 'responsible' downsizing reduces the negative impacts of downsizing on the surviving employees (Cornea et al., 2021; Tsai & Yen, 2020). In the case of responsible downsizing, the firm performs an employee downsizing activity while using Corporate Social Responsibility policies (Cornea et al., 2021). Regarding post-employee downsizing digital innovation performance, it would be interesting to discover what role responsible downsizing can play in this.

6 Conclusion

This research adds to the discussion of the role that organizational learning can play in the context of employee downsizing and its effect on a firm's digital innovation performance. Furthermore, it explores the field of digital M&A by using it as the context for this research. This research builds on the concepts of organizational learning (Levitt & March, 1988), which argues that firms can learn from previous experiences and can use this to enhance their future performance. Based on the work of Bergh and Lim (2008), it was argued that firms that accumulated downsizing experience would have higher digital innovation performance after the focal employee downsizing activity than firms that did not have this. However, the analyses of this research show different results. Namely, that the number of prior employee downsizing activities ten years prior to the focal employee downsizing does not have a significant effect on the firm's post-employee downsizing digital innovation performance. However, partial support is found that having employee downsizing experience overall within the ten years prior to the focal employee downsizing activity is of positive significant impact to the firm's post-employee downsizing digital innovation performance. Furthermore, the results partially support the understanding that leadership stability

displays an inverted U-shaped relationship with the firm's post-employee downsizing digital innovation performance. However, leadership stability did not show to negatively impact the relationship between the scale of employee downsizing and the firm's digital innovation performance. On the contrary, evidence was found that there is partial support that it might even increase the relationship. This research provides new knowledge that enables firms and researchers to better understand the role that organizational learning can play in employee downsizing and a firm's digital innovation performance.

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References

- Aalbers, R. (2020). Rewiring the intrafirm network under downsizing: The role of tie loss on discretionary tie formation. *Long Range Planning*, 53(3), Article 101858.
<https://doi.org/10.1016/j.lrp.2018.11.002>
- Aalbers, R., Dolfsma, W., & Koppius, O. (2014). Rich Ties and Innovative Knowledge Transfer within a Firm. *British Journal of Management*, 25(4), 833-848.
<https://doi.org/10.1111/1467-8551.12040>
- Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal*, 22(3), 197-220.
<https://doi.org/10.1002/smj.157>
- Allgood, S., & Farrell, K. A. (2000). The effect of CEO tenure on the relation between firm performance and turnover. *Journal of financial research*, 23(3), 373-390.
- Argote, L. (2011). Organizational learning research: Past, present and future. *Management learning*, 42(4), 439-446.
- Argote, L., Lee, S., & Park, J. (2021). Organizational Learning Processes and Outcomes: Major Findings and Future Research Directions. *Management science*, 67(9), 5399-5429.
<https://doi.org/10.1287/mnsc.2020.3693>
- Argote, L., & Miron-Spektor, E. (2011). Organizational Learning: From Experience to Knowledge. *Organization Science*, 22(5), 1123-1137.
<https://doi.org/10.1287/orsc.1100.0621>
- Balkin, D. B., Markman, G. D., & Gomez-Mejia, L. R. (2000). Is CEO pay in high-technology firms related to innovation? *Academy of Management Journal*, 43(6), 1118-1129.
- Barkema, H. G., & Schijven, M. (2008). Toward unlocking the full potential of acquisitions: The role of organizational restructuring. *Academy of Management Journal*, 51(4), 696-722.
[Go to ISI://WOS:000258952800005](https://doi.org/10.2307/2589528)
- Bergh, D. D., & Lim, E. N. K. (2008). Learning how to restructure: Absorptive capacity and improvisational views of restructuring actions and performance. *Strategic Management Journal*, 29(6), 593-616. <https://doi.org/10.1002/smj.676>
- Bergström, O., & Diedrich, A. (2011). Exercising Social Responsibility in Downsizing: Enrolling and Mobilizing Actors at a Swedish High-Tech Company. *Organization Studies*, 32(7), 897-919. <https://doi.org/10.1177/0170840611407019>

- Bhussar, M. S., Sexton, J. C., Zorn, M. L., & Song, Y. (2022). High-tech acquisitions: How acquisition pace, venture maturity, and founder retention influence firm innovation. *Journal of Business Research*, 142, 620-635.
<https://doi.org/10.1016/j.jbusres.2022.01.007>
- Bielig, A. (2022). The Propensity to Patent Digital Technology: Mirroring Digitalization Processes in Germany with Intellectual Property in a European Perspective. *Journal of the Knowledge Economy*. <https://doi.org/10.1007/s13132-022-00986-z>
- Bommer, M., & Jalajas, D. S. (1999). The threat of organizational downsizing on the innovative propensity of R & D professionals. *R & D Management*, 29(1), 27-34.
<https://doi.org/10.1111/1467-9310.00114>
- Brauer, M., & Laamanen, T. (2014). Workforce Downsizing and Firm Performance: An Organizational Routine Perspective. *Journal of Management Studies*, 51(8), 1311-1333.
<https://doi.org/10.1111/joms.12074>
- Brauer, M., Mammen, J., & Luger, J. (2017). Sell-Offs and Firm Performance: A Matter of Experience? *Journal of Management*, 43(5), 1359-1387.
<https://doi.org/10.1177/0149206314552452>
- Brown, S. L., & Eisenhardt, K. M. (1995). PRODUCT DEVELOPMENT - PAST RESEARCH, PRESENT FINDINGS, AND FUTURE-DIRECTIONS. *Academy of Management Review*, 20(2), 343-378. <https://doi.org/10.2307/258850>
- Bughin, J., Hazan, E., Lund, S., Dahlström, P., Wiesinger, A., & Subramaniam, A. (2018). Skill shift: Automation and the future of the workforce. In *McKinsey Global Institute* (Vol. 1, pp. 3-84).
- Calipha, R., Tarba, S., & Brock, D. (2010). MERGERS AND ACQUISITIONS: A REVIEW OF PHASES, MOTIVES, AND SUCCESS FACTORS. In C. L. Cooper & S. Finkelstein (Eds.), *Advances in Mergers and Acquisitions*, Vol 9 (Vol. 9, pp. 1-24).
[https://doi.org/10.1108/s1479-361x\(2010\)0000009004](https://doi.org/10.1108/s1479-361x(2010)0000009004)
- Candra, A., Priyarsono, D. S., Zulbainarni, N., & Sembel, R. (2021). Literature Review on Merger and Acquisition. *Estudios De Economia Aplicada*, 39(4).
<https://doi.org/10.25115/eea.v39i4.4627>

- Cascio, W. F., Chatrath, A., & Christie-David, R. A. (2021). ANTECEDENTS AND CONSEQUENCES OF EMPLOYEE AND ASSET RESTRUCTURING. *Academy of Management Journal*, 64(2), 587-613. <https://doi.org/10.5465/amj.2018.1013>
- Cefis, E., Marsili, O., & Rigamonti, D. (2020). In and Out of Balance: Industry Relatedness, Learning Capabilities and Post-Acquisition Innovative Performance. *Journal of Management Studies*, 57(2), 210-245. <https://doi.org/10.1111/joms.12441>
- Chen, H.-L. (2013). CEO tenure, independent directors and corporate innovation. *Journal of Applied Finance and Banking*, 3(5), 187.
- Cho, S. Y., & Arthurs, J. D. (2018). The influence of alliance experience on acquisition premiums and post-acquisition performance. *Journal of Business Research*, 88, 1-10. <https://doi.org/10.1016/j.jbusres.2018.02.022>
- Cloodt, M., Hagedoorn, J., & Van Kranenburg, H. (2006). Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries. *Research Policy*, 35(5), 642-654. <https://doi.org/10.1016/j.respol.2006.02.007>
- Cornea, D., Titova, Y., & Le Roy, J. (2021). Caring for survivors: Do CSR policies matter for post-restructuring employee performance? *Business Ethics the Environment & Responsibility*. <https://doi.org/10.1111/beer.12372>
- Crossan, M., Cunha, M. P. E., Vera, D., & Cunha, J. (2005). Time and organizational improvisation. *Academy of Management Review*, 30(1), 129-145. <https://doi.org/10.5465/amr.2005.15281441>
- Dasgupta, M., & Gupta, R. K. (2009). Innovation in Organizations: A Review of the Role of Organizational Learning and Knowledge Management. *Global Business Review*, 10(2), 203-224. <https://doi.org/10.1177/097215090901000205>
- Datta, D. K., Guthrie, J. P., Basuil, D., & Pandey, A. (2010). Causes and Effects of Employee Downsizing: A Review and Synthesis. *Journal of Management*, 36(1), 281-348. <https://doi.org/10.1177/0149206309346735>
- Datta, P., & Roumani, Y. (2015). Knowledge-acquisitions and post-acquisition innovation performance: a comparative hazards model [Article]. *European Journal of Information Systems*, 24(2), 202-226. <https://doi.org/10.1057/ejis.2014.32>

- De Man, A. P., & Duysters, G. (2005). Collaboration and innovation: a review of the effects of mergers, acquisitions and alliances on innovation. *Technovation*, 25(12), 1377-1387. <https://doi.org/10.1016/j.technovation.2004.07.021>
- Desai, V., & Madsen, P. (2019). Take Your Time? How Activity Timing Affects Organizational Learning and Performance Outcomes. *Organization Science*. <https://doi.org/10.1287/orsc.2021.1490>
- Du, M., Kwabi, F., & Yang, T. L. (2021). State ownership, prior experience and performance: a comparative analysis of Chinese domestic and cross-border acquisitions. *International Journal of Accounting and Information Management*, 29(3), 472-491. <https://doi.org/10.1108/ijaim-01-2021-0027>
- Edmondson, A. (1999). Psychological safety and learning behavior in work teams. *Administrative Science Quarterly*, 44(2), 350-383. <https://doi.org/10.2307/2666999>
- Eisenhardt, K. M., & Tabrizi, B. N. (1995). ACCELERATING ADAPTIVE PROCESSES - PRODUCT INNOVATION IN THE GLOBAL COMPUTER INDUSTRY. *Administrative Science Quarterly*, 40(1), 84-110. <https://doi.org/10.2307/2393701>
- Falk, G., Romero, P. D., Nicchitta, I. A., & Nyhof, E. (2021). *Unemployment Rates During the COVID-19 Pandemic*. (R46554). Retrieved from <https://sgp.fas.org/crs/misc/R46554.pdf>
- Farkas Charles, M., & Suzy, W. (1998). The Ways Chief Executive Officers Lead. *HARVARD BUSINESS REVIEW ON LEADERSHIP*, Harvard Business School Press, USA.
- Gandolfi, F., & Oster, G. (2010). How does downsizing impact the innovative capability of a firm? A contemporary discussion with conceptual frameworks. *International Journal of Innovation and Learning*, 8(2), 127-148. <https://doi.org/10.1504/ijil.2010.034346>
- Ghobakhloo, M., & Fathi, M. (2020). Corporate survival in Industry 4.0 era: the enabling role of lean-digitized manufacturing. *Journal of Manufacturing Technology Management*, 31(1), 1-30. <https://doi.org/10.1108/jmtm-11-2018-0417>
- Gunday, G., Ulusoy, G., Kilic, K., & Alpkan, L. (2011). Effects of innovation types on firm performance. *International Journal of Production Economics*, 133(2), 662-676. <https://doi.org/10.1016/j.ijpe.2011.05.014>

- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2020). *Multivariate Data Analysis* (Eighth Edition ed.). Cengage Learning, EMEA.
- Hambrick, D. C., & Fukutomi, G. D. (1991). The seasons of a CEO's tenure. *Academy of Management Review*, *16*(4), 719-742.
- Hanelt, A., Firk, S., Hildebrandt, B., & Kolbe, L. M. (2021). Digital M&A, digital innovation, and firm performance: an empirical investigation [Article]. *European Journal of Information Systems*, *30*(1), 3-26. <https://doi.org/10.1080/0960085X.2020.1747365>
- Hayward, M. L. A. (2002). When do firms learn from their acquisition experience? Evidence from 1990-1995. *Strategic Management Journal*, *23*(1), 21-39. <https://doi.org/10.1002/smj.207>
- Herrmann, P., & Datta, D. K. (2006). CEO experiences: Effects on the choice of FDI entry mode. *Journal of Management Studies*, *43*(4), 755-778.
- Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Information and Organization*, *28*(1), 52-61. <https://doi.org/10.1016/j.infoandorg.2018.02.004>
- Hitt, M., Harrison, J., Ireland, R. D., & Best, A. (1998). Attributes of successful and unsuccessful acquisitions of US firms. *British Journal of Management*, *9*(2), 91-114.
- Huber, G. P. (1991). ORGANIZATIONAL LEARNING: THE CONTRIBUTING PROCESSES AND THE LITERATURES. *Organization Science*, *2*(1), 88-115. <https://doi.org/10.1287/orsc.2.1.88>
- Jaw, Y.-L., & Lin, W.-T. (2009). Corporate elite characteristics and firm's internationalization: CEO-level and TMT-level roles. *The International Journal of Human Resource Management*, *20*(1), 220-233.
- Jimenez-Jimenez, D., & Sanz-Valle, R. (2011). Innovation, organizational learning, and performance. *Journal of Business Research*, *64*(4), 408-417. <https://doi.org/10.1016/j.jbusres.2010.09.010>
- Johnson, R. A. (1996). Antecedents and outcomes of corporate refocusing. *Journal of Management*, *22*(3), 439-483. <https://doi.org/10.1177/014920639602200304>
- Kane, A. A., Argote, L., & Levine, J. M. (2005). Knowledge transfer between groups via personnel rotation: Effects of social identity and knowledge quality. *Organizational*

Behavior and Human Decision Processes, 96(1), 56-71.

<https://doi.org/10.1016/j.obhdp.2004.09.002>

Kim, C., Song, J., & Nerkar, A. (2012). Learning and innovation: Exploitation and exploration trade-offs. *Journal of Business Research*, 65(8), 1189-1194.

<https://doi.org/10.1016/j.jbusres.2011.07.006>

KNAW, NFW, NWO, TO2-federatie, Hogescholen, V., & VSNU. (2018). *Nederlandse gedragscode wetenschappelijke integriteit* <https://doi.org/https://doi.org/10.17026/dans-2cj-nvwu>

Kohli, R., & Melville, N. P. (2019). Digital innovation: A review and synthesis. *Information Systems Journal*, 29(1), 200-223. <https://doi.org/10.1111/isj.12193>

Krishnan, H. A., Hitt, M. A., & Park, D. (2007). Acquisition premiums, subsequent workforce reductions and post-acquisition performance. *Journal of Management Studies*, 44(5), 709-732. <https://doi.org/10.1111/j.1467-6486.2006.00672.x>

Krutova, O., Koistinen, P., Turja, T., Melin, H., & Sarkikoski, T. (2021). Two sides, but not of the same coin: digitalization, productivity and unemployment. *International Journal of Productivity and Performance Management*. <https://doi.org/10.1108/ijppm-05-2020-0233>

Lakshman, C., Ramaswami, A., Alas, R., Kabongo, J., & Rajendran Pandian, J. (2014). *Ethics Trumps Culture? A Cross-National Study of Business Leader Responsibility for Downsizing and CSR Perceptions* [Report](01674544). <https://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=98861976&site=ehost-live>

Lane, P. J., Koka, B. R., & Pathak, S. (2006). The reification of absorptive capacity: A critical review and rejuvenation of the construct. *Academy of Management Review*, 31(4), 833-863. <https://doi.org/10.5465/amr.2006.22527456>

Levinthal, D. A., & March, J. G. (1993). The myopia of learning. *Strategic Management Journal*, 14(S2), 95-112.

Levitt, B., & March, J. G. (1988). ORGANIZATIONAL LEARNING. *Annual Review of Sociology*, 14, 319-340. <https://doi.org/10.1146/annurev.so.14.080188.001535>

Li, H., Chen, Q. X., Hong, L. Y., & Zhou, Q. (2019). Asset restructuring performance prediction for failure firms. *Journal of Corporate Accounting and Finance*, 30(4), 25-42.

<https://doi.org/10.1002/jcaf.22409>

- Lin, B. X., Lee, Z. H., & Gibbs, L. G. (2008). Operational restructuring: reviving an ailing business. *Management Decision*, 46(3-4), 539-552.
<https://doi.org/10.1108/00251740810865049>
- Luo, X., Kanuri, V. K., & Andrews, M. (2014). How does CEO tenure matter? The mediating role of firm-employee and firm-customer relationships. *Strategic Management Journal*, 35(4), 492-511.
- March, J. G. (1991). EXPLORATION AND EXPLOITATION IN ORGANIZATIONAL LEARNING. *Organization Science*, 2(1), 71-87. <https://doi.org/10.1287/orsc.2.1.71>
- Marques, T., Galende, J., Cruz, P., & Ferreira, M. P. (2014). Surviving downsizing and innovative behaviors: a matter of organizational commitment. *International Journal of Manpower*, 35(7), 930-955. <https://doi.org/10.1108/ijm-03-2012-0049>
- McCarthy, K. J., & Aalbers, H. L. (2016). Technological acquisitions: The impact of geography on post-acquisition innovative performance. *Research Policy*, 45(9), 1818-1832.
<https://doi.org/10.1016/j.respol.2016.05.012>
- McClelland, P. L., Liang, X., & Barker III, V. L. (2010). CEO commitment to the status quo: Replication and extension using content analysis. *Journal of Management*, 36(5), 1251-1277.
- Mellahi, K., & Wilkinson, A. (2008). A STUDY OF THE ASSOCIATION BETWEEN DOWNSIZING AND INNOVATION DETERMINANTS. *International Journal of Innovation Management*, 12(4), 677-698. <https://doi.org/10.1142/s1363919608002163>
- Miceli, A., Hagen, B., Riccardi, M. P., Sotti, F., & Settembre-Blundo, D. (2021). Thriving, Not Just Surviving in Changing Times: How Sustainability, Agility and Digitalization Intertwine with Organizational Resilience. *Sustainability*, 13(4), Article 2052.
<https://doi.org/10.3390/su13042052>
- Miller, D. (1991). Stale in the saddle: CEO tenure and the match between organization and environment. *Management science*, 37(1), 34-52.
- Miller, D. (1993). Some organizational consequences of CEO succession. *Academy of Management Journal*, 36(3), 644-659.
- Miller, D., & Shamsie, J. (2001). Learning across the life cycle: Experimentation and performance among the Hollywood studio heads. *Strategic Management Journal*, 22(8), 725-745.

- Mishra, A. K., Mishra, K. E., & Spreitzer, G. M. (2009). Downsizing the Company Without Downsizing Morale. *Mit Sloan Management Review*, 50(3), 39-+. <Go to ISI>://WOS:000265012500011
- Munoz-Bullon, F., & Sanchez-Bueno, M. J. (2010). Downsizing implementation and financial performance. *Management Decision*, 48(7-8), 1181-1197.
<https://doi.org/10.1108/00251741011076735>
- Musteen, M., Barker III, V. L., & Baeten, V. L. (2010). The influence of CEO tenure and attitude toward change on organizational approaches to innovation. *The Journal of Applied Behavioral Science*, 46(3), 360-387.
- Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). DIGITAL INNOVATION MANAGEMENT: REINVENTING INNOVATION MANAGEMENT RESEARCH IN A DIGITAL WORLD. *Mis Quarterly*, 41(1), 223-238.
<https://doi.org/10.25300/misq/2017/41:1.03>
- Paruchuri, S., Nerkar, A., & Hambrick, D. C. (2006). Acquisition integration and productivity losses in the technical core: Disruption of inventors in acquired companies. *Organization Science*, 17(5), 545-562. <https://doi.org/10.1287/orsc.1060.0207>
- Pedersen, E. R. G., Gwozdz, W., & Hvass, K. K. (2018). Exploring the Relationship Between Business Model Innovation, Corporate Sustainability, and Organisational Values within the Fashion Industry. *Journal of Business Ethics*, 149(2), 267-284.
<https://doi.org/10.1007/s10551-016-3044-7>
- Pesch, R., Endres, H., & Bouncken, R. B. (2021). Digital product innovation management: Balancing stability and fluidity through formalization. *Journal of Product Innovation Management*.
- Petkovska, T. (2015). THE ROLE AND IMPORTANCE OF INNOVATION IN BUSINESS OF SMALL AND MEDIUM ENTERPRISES [Article]. *Economic Development / Ekonomiski Razvoj*, 17(1/2), 55-74.
<https://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=108488417&site=ehost-live>
- Powell, R., & Yawson, A. (2007). Are corporate restructuring events driven by common factors? Implications for takeover prediction. *Journal of Business Finance & Accounting*, 34(7-8), 1169-1192.

- Rajapathirana, R. P. J., & Hui, Y. (2018). Relationship between innovation capability, innovation type, and firm performance. *Journal of Innovation & Knowledge*, 3(1), 44-55.
<https://doi.org/10.1016/j.jik.2017.06.002>
- Renneboog, L., & Szilagy, P. G. (2008). Corporate restructuring and bondholder wealth. *European Financial Management*, 14(4), 792-819. <https://doi.org/10.1111/j.1468-036X.2007.00414.x>
- Rosenbusch, N., Brinckmann, J., & Bausch, A. (2011). Is innovation always beneficial? A meta-analysis of the relationship between innovation and performance in SMEs. *Journal of Business Venturing*, 26(4), 441-457. <https://doi.org/10.1016/j.jbusvent.2009.12.002>
- Said, T., Le Louarn, J.-Y., & Tremblay, M. (2007). The performance effects of major workforce reductions: longitudinal evidence from North America [Article]. *International Journal of Human Resource Management*, 18(12), 2075-2094.
<https://doi.org/10.1080/09585190701695234>
- Simsek, Z. (2007). CEO tenure and organizational performance: An intervening model. *Strategic Management Journal*, 28(6), 653-662.
- Souder, D., Simsek, Z., & Johnson, S. G. (2012). The differing effects of agent and founder CEOs on the firm's market expansion. *Strategic Management Journal*, 33(1), 23-41.
- Sun, Z. J. (2014). Domestic technological acquisitions and the innovation performance of acquiring firms. *Journal of Chinese Economic and Business Studies*, 12(2), 149-170.
<https://doi.org/10.1080/14765284.2014.900944>
- Tangpong, C., Abebe, M., & Li, Z. (2015). A temporal approach to retrenchment and successful turnaround in declining firms. *Journal of Management Studies*, 52(5), 647-677.
- Tsai, C. F., & Yen, Y. F. (2020). Moderating effect of employee perception of responsible downsizing on job satisfaction and innovation commitment. *International Journal of Human Resource Management*, 31(15), 1913-1937.
<https://doi.org/10.1080/09585192.2018.1424014>
- Vera, D., & Crossan, M. (2005). Improvisation and innovative performance in teams. *Organization Science*, 16(3), 203-224. <https://doi.org/10.1287/orsc.1050.0126>
- Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *Journal of Strategic Information Systems*, 28(2), 118-144.
<https://doi.org/10.1016/j.jsis.2019.01.003>

- Virany, B., Tushman, M. L., & Romanelli, E. (1992). Executive succession and organization outcomes in turbulent environments: An organization learning approach. *Organization Science*, 3(1), 72-91.
- Wang, J., & Bai, T. (2021). How digitalization affects the effectiveness of turnaround actions for firms in decline. *Long Range Planning*, 102140.
- Wu, S., Levitas, E., & Priem, R. L. (2005). CEO tenure and company invention under differing levels of technological dynamism. *Academy of Management Journal*, 48(5), 859-873.
- Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review*, 27(2), 185-203.
<https://doi.org/10.2307/4134351>
- Zhang, Y., & Rajagopalan, N. (2004). When the known devil is better than an unknown god: An empirical study of the antecedents and consequences of relay CEO successions. *Academy of Management Journal*, 47(4), 483-500.
- Zhu, J. N., & Zhang, D. (2017). Does Corruption Hinder Private Businesses? Leadership Stability and Predictable Corruption in China. *Governance-an International Journal of Policy Administration and Institutions*, 30(3), 343-363. <https://doi.org/10.1111/gove.12220>
- Zollo, M., & Singh, H. (2004). Deliberate learning in corporate acquisitions: Post-acquisition strategies and integration capability in US bank mergers. *Strategic Management Journal*, 25(13), 1233-1256. <https://doi.org/10.1002/smj.426>

Appendix A

Table A1

Results regression analyses of a year prior to downsizing to the year of downsizing

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Controls						
Intercept	0.70 [†] (0.37)	0.60 (0.40)	0.52 (0.37)	0.19 (0.36)	0.62 (0.41)	0.34 (0.38)
Firm Age	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Firm Size	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Firm ROA	-0.02 (0.01)	-0.02 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.02 (0.01)	-0.02 (0.01)
Firm R&D	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Time Between M&A and Downsizing	-0.03 (0.04)	-0.03 (0.04)	-0.02 (0.04)	-0.01 (0.04)	-0.03 (0.04)	-0.02 (0.04)
Explanatory variables						
Scale of Downsizing		14.02 (17.51)	11.70 (20.48)	21.53* (9.47)	9.13 (23.31)	14.91 (59.74)
Number of previous downsizing experience			0.05 (0.08)			0.15 (0.18)
Scale of Downsizing x Number of previous downsizing experience			9.36 (25.24)			-0.90 (80.56)
No Earlier Downsizing Experience				0.10 (0.17)		0.38 (0.41)
Scale of Downsizing x No Earlier Downsizing Experience				-28.71 (22.14)		-25.84 (170.792)
CEO Tenure					0.00 (0.00)	0.00 (0.01)
Scale of Downsizing x CEO Tenure					0.75 (0.61)	0.90 (1.09)
Adjusted R^2	0.04	0.06	0.06	0.05	0.07	0.08
F	1.63	1.81	1.68	1.50	1.77 [†]	1.60
N	81	81	81	81	81	81

Note. [†] $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table A2*Results regression analyses of a year prior to downsizing to a year after downsizing*

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Controls						
Intercept	1.42** (0.49)	1.39* (0.50)	1.54** (0.54)	1.55** (0.49)	1.50** (0.49)	1.68** (0.52)
Firm Age	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Firm Size	-0.14* (0.07)	-0.14† (0.07)	-0.16* (0.08)	-0.16* (0.06)	-0.15* (0.06)	-0.18** (0.07)
Firm ROA	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
Firm R&D	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Time Between M&A and Downsizing	-0.03 (0.03)	-0.03 (0.03)	-0.03 (0.04)	-0.04 (0.04)	-0.04 (0.03)	-0.04 (0.04)
Explanatory variables						
Scale of Downsizing		4.32 (7.03)	0.63 (12.84)	7.87 (7.74)	3.43 (7.34)	- ^a
Number of previous downsizing experience			0.00 (0.06)			0.02 (0.08)
Scale of Downsizing x Number of previous downsizing experience			8.34 (15.45)			7.56 (9.95)
No Earlier Downsizing Experience				0.02 (0.15)		0.05 (0.20)
Scale of Downsizing x No Earlier Downsizing Experience				-20.34 (19.12)		-4.56 (21.03)
CEO Tenure					0.00 (0.00)	0.00 (0.00)
Scale of Downsizing x CEO Tenure					0.16 (0.41)	0.15 (0.42)
Adjusted R^2	0.09	0.08	0.07	0.08	0.08	0.05
F	2.33†	1.99†	1.62	1.66	1.71	1.33
N	66	66	66	66	66	66

Note. † $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.^a As *Scale of downsizing* had a VIF value of 12.89, the variable was omitted from the total model.

Table A3*Results regression analyses of a year prior to downsizing to three years after downsizing*

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Controls						
Intercept	0.38 (0.45)	0.29 (0.46)	0.23 (0.47)	0.33 (0.43)	0.37 (0.57)	0.37 (0.55)
Firm Age	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)	0.00 (0.00)
Firm Size	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Firm ROA	0.00 (0.02)	0.01 (0.02)	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)	-0.01 (0.00)
Firm R&D	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Time Between M&A and Downsizing	0.01 (0.08)	0.02 (0.07)	0.05 (0.08)	0.06 (0.08)	0.06 (0.09)	0.07 (0.09)
Explanatory variables						
Scale of Downsizing			23.39 [†] (13.41)	-0.58 (0.08)	9.15 (15.58)	- ^a
Number of previous downsizing experience			0.04 (0.14)			-0.02 (0.21)
Scale of Downsizing x Number of previous downsizing experience			-30.09 [†] (16.60)			7.72 (20.21)
No Earlier Downsizing Experience				-0.14 (0.33)		-0.07 (0.53)
Scale of Downsizing x No Earlier Downsizing Experience				75.93* (34.45)		89.13* (43.27)
CEO Tenure					0.00 (0.01)	0.00 (0.01)
Scale of Downsizing x CEO Tenure					-2.65 (4.96)	-2.83 (4.67)
Adjusted R ²	-0.03	-0.04	0.03	0.09	-0.07	0.05
F	0.77	0.80	1.12	1.41	0.72	1.18
N	36	36	36	36	36	36

Note. [†] $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$. ^a As *Scale of downsizing* had a VIF value of 15.83, the variable was omitted from the total model.

Appendix B

Table B1

Overview assumptions per model

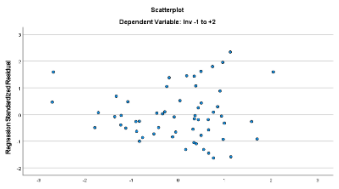
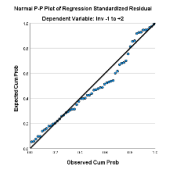
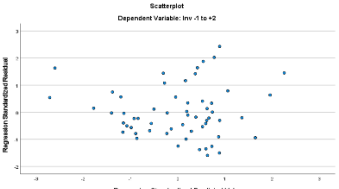
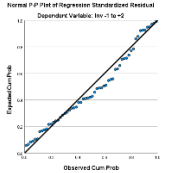
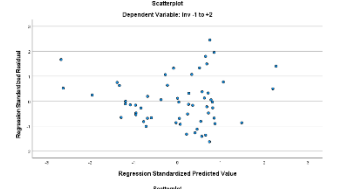
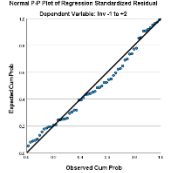
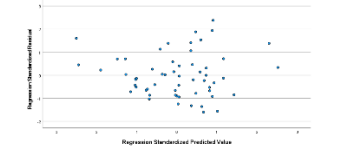
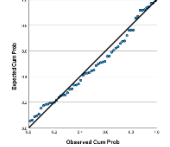
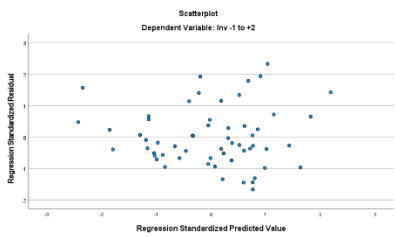
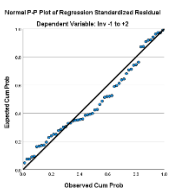
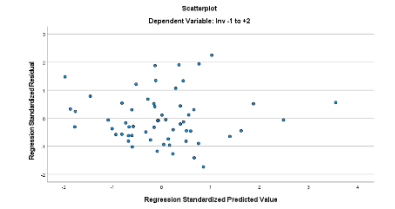
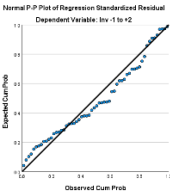
Model number	Cook's Distance value	Assumption 1 and 2 (scatterplots)	Assumption 2 (Modified Breusch-Pagan test)	Assumption 3 (P-P plot)	Assumption 4 (Durban-Watson statistic)
1	0.111		0.018 [*]		1.564
2	0.152		0.087 [†]		1.559
3	0.189		0.100		1.561
4	0.111		0.084 [†]		1.464

Table B1 (continued).

5	10.086		0.057 [†]		1.616
6	6.776		0.307		1.414

Note. [†] $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.