

The Role of Digital Technologies Regarding Employee Intrapreneurial and Innovative Behavior

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List of Abbreviations

CI	95% bootstrap confidence interval of the indirect effect
coeff.	within-person level path coefficient
IT	information technology
Satorra-Bentler scaled chi-square difference	$\Delta \text{S-B } \chi^2$

Abstract

Drawing on a resource perspective, this thesis scrutinizes the role of digital technologies regarding employee intrapreneurial and innovative behavior. This is done by conducting four independent empirical studies which examine how digital technologies foster and inhibit employee intrapreneurial and innovative behavior. The first study investigates employee-perceived information technology support for innovation, work overload, and invasion of privacy as mediators of the relationship between digital affordances and employee corporate entrepreneurship participation likelihood. The second study examines the relationship between digital technology support and employee intrapreneurial behavior and how this relationship is moderated by management support for innovation and intrapreneurial self-efficacy. Analyzing employee techno-work engagement and employee-perceived techno-strain as mediators, the third study investigates the relationships of employee-perceived digital technology usefulness and complexity with employee innovative performance. Finally, the fourth study examines the indirect effects of perceived daily techno-support and techno-stressors on daily employee innovative behavior through daily high-activated moods. Findings revealed digital affordances to foster employee corporate entrepreneurship participation likelihood through employee-perceived information technology support for innovation and reduced work overload perceptions. Support by different digital technologies was also found to promote employee intrapreneurial behavior, but its relative impact varied with different levels of management support for innovation and intrapreneurial self-efficacy. Moreover, employee-perceived digital technology usefulness fostered employee innovative performance through employee techno-work engagement, while employee-perceived digital technology complexity had negative sequential indirect effects through employee-perceived digital technology usefulness and employee-perceived techno-strain

on the one hand and employee techno-work engagement on the other hand. Perceived daily techno-support had a beneficial effect through daily high-activated positive mood. Perceived daily techno-stressors fostered daily employee innovative behavior through daily high-activated negative mood but inhibited that behavior through daily high-activated positive mood. Thus, findings indicate that by offering potentials for both resource gains and losses, digital technologies might be a double-edged sword for employee intrapreneurial and innovative behavior. Hence, with this, the thesis advances the research on employee intrapreneurial and innovative behavior as well as the digital entrepreneurship and innovation literature.

1. Introduction

1.1 Research Problem and Objective of the Work

Globalization and technological, regulatory, and economic changes have led to increasing market challenges and a complex and turbulent business environment (Ardito et al., 2015; Hollen et al., 2013). Hence, modern organizations must adapt to unexpected situations or take advantage of new opportunities to ensure their effectiveness, performance, success, and long-term survival (Anderson et al., 2014; Kanter, 1988; Madrid et al., 2014; West & Farr, 1990). Fostering employee intrapreneurial behavior (see, e.g., Antoncic & Hisrich, 2003; Blanka, 2019; Gawke et al., 2017, 2018; Ireland et al., 2003; Kuratko, Morris, & Schindehutte, 2015; Morris, Kuratko, & Covin, 2011; Morris, Webb, & Franklin, 2011) and employee innovative behavior (Anderson et al., 2014; M. M. Hammond et al., 2011; Janssen, 2000; Kanter, 1988; Madrid et al., 2014) provides ways for companies to successfully adapt and proactively act upon environmental opportunities such as demographic, technological, or regulatory changes.

Employee intrapreneurial and innovative behaviors are closely related (Junglas et al., 2019), and both behaviors are aimed at organizational change and improvement (Gawke et al., 2018). *Employee intrapreneurial behavior* refers to “an individual employee’s agentic and anticipatory behaviors aimed at creating new businesses for the organization (i.e., venture behavior) and enhancing an organization’s ability to react to internal and external advancements (i.e., strategic renewal behavior)” (Gawke et al., 2017, p. 89). *Employee innovative behavior* is the exploration, generation, championing, and implementation of innovative ideas by employees (de Jong & den Hartog, 2010; Janssen, 2000; Scott & Bruce, 1994). However, while intrapreneurial and innovative employee behaviors both aim at the creation of something new, only intrapreneurship also focuses on the emergence of new ventures (Antoncic & Hisrich, 2003).

In this dissertation, two types of employee intrapreneurial behavior are examined: employees' likelihood to join corporate entrepreneurial projects and employees' likelihood to start intrapreneurial projects on their own accord, which covers the more proactive side of employee intrapreneurship (see, e.g., Gawke et al., 2017). Considering that intrapreneurial and innovative behaviors hold the promise of securing their competitive advantage, organizations need to know how they can foster these behaviors (Blanka, 2019, Hornsby et al., 2002; Pieterse et al., 2010).

Previous research (see the reviews of Blanka, 2019 and Neessen et al., 2019) has already identified a range of individual factors determining employee intrapreneurial behavior: human capital-related factors (e.g., abilities and skills, knowledge, past experiences, self-efficacy), personal characteristics (e.g., personality traits, values), motivation-related factors (e.g., personal initiative), individuals' feelings of organizational affiliation (e.g., organizational commitment and identification, job satisfaction), and perceptions (e.g., regarding risk and uncertainty). Social factors found to be antecedents of employee intrapreneurial behavior (Blanka, 2019; Neessen et al., 2019) are leadership and supervision styles (e.g., transformational leadership, authentic leadership) and network-related factors (e.g., internal bonding networks, external bridging networks). Organizational factors that foster employee intrapreneurial activities are management support, a supportive culture and organizational structure, rewards and reinforcements, autonomy and work discretion, and providing resources such as time or financial support (Blanka, 2019, Hornsby et al., 2002; Neessen et al., 2019).

Similarly, previous research (Anderson et al., 2014; Binnewies & Gromer, 2012) has found employee innovative behavior to be impacted by individual factors such as human capital-related factors (e.g., abilities, knowledge, and self-efficacy), personal characteristics (e.g., personality traits, goal-orientations, values, thinking styles, self-concepts, and identities),

motivation-related factors (expected image gains, positive performance outcomes, affect and mood as motivating psychological states, and personal initiative), and individuals' feelings of organizational affiliation (e.g., organizational identification and job involvement). Social factors that foster employee innovative behavior (Anderson et al., 2014) are leadership and supervision styles (e.g., transformational leadership, supervisory support, and non-close monitoring), network-related factors (e.g., social networks), and other factors such as customer influence, feedback, and evaluation. Finally, organizational factors found to be beneficial for employee innovative activities (see Anderson et al., 2014; Riaz et al., 2018) are management support, job complexity, routinization, organizational goals, and job requirements (e.g., time pressure).

However, changing how ideas are generated and disseminated, technological advancements, and especially the near-ubiquitous spread of digital technologies, might also have the potential to contribute to the stimulation of entrepreneurial and innovative activities within organizations (Anderson et al., 2014; Junglas et al., 2019). Thus, the burgeoning research on digital entrepreneurship and digital innovation has recently suggested that digital technologies foster entrepreneurship (e.g., Autio et al., 2018; Nambisan, 2017; von Briel et al., 2018), intrapreneurship (e.g., Arvidsson & Mønsted, 2018; Baum & Rabl, 2019), and innovation (e.g., Junglas et al., 2019; Nambisan, 2013; Nambisan et al., 2017; Yoo et al., 2012). *Digital entrepreneurship* is defined as the pursuit of opportunities based on the use of digital technologies (Davidson & Vaast, 2010, p. 2979). *Digital technologies*, which can be defined as “products or services that are either embodied in information and communication technologies or enabled by them” (Lyytinen et al., 2016, p. 49), have a large influence on the evolution of modern business models (see, e.g., Ojala, 2016). Thus, digital entrepreneurship involves the emergence of new ventures and the transformation of existing businesses via the creation of new digital technologies and/or the finding of new ways of using such technologies (Shen et al.,

2018). *Digital innovation* refers to “the creation of (and consequent change in) market offerings, business processes, or models that result from the use of digital technology” (Nambisan et al., 2017, p. 224).

Digitization has changed entrepreneurial and innovation outcomes and processes (Nambisan, 2017; Nambisan et al., 2017). On the one hand, digitization blurs the structural boundaries of a product or service, such as its features, scope, and market reach (Nambisan, 2017). On the other hand, it alters the spatial and temporal boundaries of entrepreneurial and innovative processes, such as when and where entrepreneurial or innovative activities are carried out (Nambisan, 2017). Moreover, with digitization, entrepreneurial and innovation agency are less predefined, shifting from a set of focal agents to dynamic collectives with different goals, motives, and capabilities (Nambisan et al., 2017). This change has led to a broader, more diverse, and continuously evolving set of entrepreneurial or innovative actors (Nambisan, 2017). Finally, digitization results in less demarcation and an increasingly complex interaction between innovation processes and outcomes, dissolving the boundaries between them (Nambisan et al., 2017). These shifting boundaries entail the emergence and evolution of new entrepreneurial and innovative opportunities (Nambisan, 2017).

To explain the new opportunities prompted by digital technologies, scholars have examined their specific characteristics and affordances. Gustavsson and Ljungberg (2018) provide an overview of the characteristics of digital technologies that distinguish them from other technologies and that cause the emergence of new entrepreneurial activities. First, digital technologies can be programmed and re-programmed (Kallinikos et al., 2013; Yoo et al., 2010, 2012). This allows entrepreneurs, intrapreneurs, and innovative employees to change existing digital technologies or create new ones (Gustavsson & Ljungberg, 2018). Second, digital technologies are combinatorial (Kallinikos et al., 2013) enabling their combination in novel ways

(Gustavsson & Ljungberg, 2018). Third, digital technologies are interoperable (Yoo et al., 2010, 2012), allowing the connection of previously unconnected digital technologies (Gustavsson & Ljungberg, 2018). Fourth, digital technologies are editable (Kallinikos et al., 2013), allowing content to be created, changed, or updated (Gustavsson & Ljungberg, 2018). Fifth, the interactivity of digital technologies (Kallinikos et al., 2013) provides actors with the opportunity to interact with their functions and affordances to facilitate their day-to-day work (Gustavsson & Ljungberg, 2018).

With these characteristics, digital technologies create three key affordances that influence the effective pursuit of entrepreneurial and innovation opportunities: de-coupling, generativity, and disintermediation (Autio et al., 2018). The de-coupling between form and function renders digital technologies inherently flexible because the inputs, instruction sets, and outputs of digital technologies are all expressed in the form of bits (Autio et al., 2018). This makes digital technologies reprogrammable, increases the possible combinations of their capabilities, and reduces the importance of asset specificity (Autio et al., 2018; Tilson et al., 2010; Yoo et al., 2010). Furthermore, digital technologies enable direct interactions promoting disintermediation (Autio et al., 2018). Thus, by allowing the bypassing of intermediaries, digital technologies make it possible to be independent of location-specific value-chain assets and resources and provide opportunities for value-creating interactions with different actors (Autio et al., 2018; Bakos, 1998; Gellman, 1996; Jallat & Capek, 2001). Moreover, digital technologies promote generativity, which is the ability to enable unprompted innovative inputs from large, uncoordinated groups (Autio et al., 2018; Zittrain, 2006). As digital technologies are malleable, easy to modify and repurpose, and facilitate the combination of functionalities, they invite experimentation and thus have the power to spur further innovation (Gustavsson & Ljungberg, 2018; Nambisan, 2017). Digital technologies are thus resources for connectivity because they

reduce the cost and increase the speed of communication. However, digital technologies are also resources for convergence because they increase knowledge heterogeneity and combinability (Lyytinen et al., 2016).

Building on previous elaborations and theorizing on the characteristics and affordances of digital technologies by Nambisan (2017) and Nambisan et al. (2017), von Briel et al. (2018) suggest that digital technologies serve as external enablers of entrepreneurial activities. In their conceptual paper, von Briel et al. (2018) propose that digital technologies enable new venture creation via six mechanisms: conservation, compression, expansion, substitution, generation, and combination. They posit that digital technologies reduce the amount of general resources (conservation) and specifically reduce the time resources (compression) required to perform entrepreneurial actions. Furthermore, digital technologies increase the availability of resources (expansion) and offer the potential to replace one resource with another (substitution). Finally, they facilitate creating new digital technologies, functionalities, and business models by changing existing ones (generation) and by bundling different resources (combination) (von Briel et al., 2018). Similarly, in his literature review, Nambisan (2013) notes that digital technologies and their components can serve as enablers and triggers of product and/or service innovation.

Steininger (2019) concludes that digital technologies can play four major roles. First, they can be facilitators easing entrepreneurial operations (Steininger, 2019). For example, digital technologies can compensate for the lack of direct access to external knowledge in new ventures. They allow knowledge transfer from the founders' previous employers or prior collaborators (Boeker et al., 2019). Second, digital technologies can be mediators, connecting entrepreneurs with their clients for value creation and/or delivery via the internet (Steininger, 2019). This provides opportunities for entrepreneurs that have to operate in resource-constrained environments, for example, micro-entrepreneurs because digital technologies support awareness

creation for existing products or customer desires and facilitate the back-and-forth exchange of information between business actors (Parthiban et al., 2021). However, to best leverage this mediating role of digital technologies, organizations may need to upgrade their managerial and organizational capabilities regarding digital-technology-mediated interactions (Li et al., 2018). Third, digital technologies can be the outcome of entrepreneurial actions, and fourth, they can become a ubiquity and thus the business model itself (Steiniger, 2019).

Nambisan and Baron (2019) have shown that membership in the digital ecosystems that facilitate entrepreneurial activities might come with costs. Digital entrepreneurs might suffer from role-conflicts leading to stress that negatively affects firm performance. Membership in those digital ecosystems requires entrepreneurs to simultaneously fill two often incompatible roles: ecosystem member and new-venture leader (Nambisan & Baron, 2019).

Regarding corporate entrepreneurship, based on the case of a Norwegian hospital, Arvidsson and Mønsted (2018) carved out four tactics that digital entrepreneurs use to generate innovation potential in organizations: concealing (developing digital technologies under the radar until investment can be justified), sequencing (the careful ordering of the consideration and alignment of motives and intentions when mobilizing support for investing in the digital technology developed), anchoring (ensuring that the digital technologies are implemented such that their use improves the conditions for change), and propagating (using their malleability to marshal many digital technologies synergistically).

Previous research on digital entrepreneurship and digital innovation has been largely conceptual (for exceptions, see, e.g., Baum and Rabl, 2019, Y. Chen et al., 2015, and Junglas et al., 2019). In their conjoint experiment, Baum and Rabl (2019) found that an organization's digital process and knowledge capital positively affect employee willingness to join a corporate entrepreneurship project. They also found that the effect of digital process capital becomes

stronger at high levels of employee personal initiative or employee digital fluency. Furthermore, high levels of employee digital fluency strengthened the effect of digital knowledge capital. Finally, the effect of an organization's digital capital on employees' willingness to join a corporate entrepreneurship project is strongest when high digital process and knowledge capital combine with employees that have high levels of personal initiative and digital fluency (Baum & Rabl, 2019). Y. Chen et al. (2015) found an organization's information technology (IT) capabilities to positively relate to organization-level corporate entrepreneurship. The authors found that this positive relationship was strengthened by the environment's competitive intensity. Junglas et al. (2019) found a positive relationship between IT consumerization behavior (e.g., using personal devices or applications for work purposes) and employee innovative behavior. However, quantitative research and thus empirical evidence in the area of digital entrepreneurship and innovation remains scarce. Scholars have noted the importance of employee intrapreneurial and innovative behavior for securing organizations' competitiveness and long-term survival (e.g., Anderson et al., 2014; Antoncic & Hisrich, 2003; Blanka, 2019; Gawke et al., 2017, 2018; M. M. Hammond et al., 2011; Ireland et al., 2003; Janssen, 2000; Madrid et al., 2014; Morris, Kuratko, & Covin, 2011; Morris, Webb, & Franklin, 2011). Despite this, research has mainly concentrated on how digital technologies create opportunities for entrepreneurship and innovation and have paid only minimal attention to how these technologies impact employee intrapreneurial and innovative behavior. Research has only recently begun to elaborate on this (Baum & Rabl, 2019; Junglas et al., 2019). This thesis is an attempt to close this gap. It examines the mechanisms through which digital technologies foster and inhibit employee intrapreneurial and innovative behavior and how organizational and individual characteristics influence the fostering role of digital technologies. In doing so, the thesis responds to research calls to shed more light on internal organizational environment antecedents of employee intrapreneurial behavior (Rigtering

et al., 2019) and to closer investigate how digital technologies enable and constrain entrepreneurship (Nambisan, 2017) and innovation (Nambisan et al., 2017). Moreover, as previous research has mostly focused on digitalization's impact on entrepreneurial activities, it complements the digital entrepreneurship literature by exploring digital technologies' effect on intrapreneurial activities.

1.2 Research Overview

This thesis will apply a resource perspective to examine the role of digital technologies in intrapreneurial and innovative behavior. It will draw on the *conservation of resources theory* (Hobfoll 1989, 2001) and the *job demands-resources model* (Bakker & Demerouti, 2007, 2017; Demerouti et al., 2001) as primary theoretical frameworks.

Previous research has already elaborated on the resource consequences of employee intrapreneurial and innovative activities. On the one hand, employee intrapreneurship might result in gains of financial resources (e.g., via profit sharing; Monsen et al., 2010). Moreover, it might also lead to gains of personal resources such as self-efficacy, optimism, and resilience because of the personal growth from overcoming the challenges associated with intrapreneurship (Gawke et al., 2017). Similarly, innovative behavior could cause employee image gains because suggesting new ideas to supervisors might result in being perceived as particularly competent and conscientious (Yuan & Woodman, 2010). On the other hand, employees that perform intrapreneurial and innovative activities have to invest additional energy and time resources because these behavior types require them to simultaneously handle their core job tasks and the challenges associated with intrapreneurial and innovative behaviors (e.g., setbacks, dealing with resistance, and convincing others of ideas; Gawke et al., 2018; Janssen, 2004).

Furthermore, research on digital technologies as facilitators (Steininger, 2019) and enablers of entrepreneurial activities (von Briel et al., 2018) and innovation (Nambisan, 2013) suggests that using digital technologies might entail potentials for resource gains and thus have positive consequences for individuals' resource pools. The affordances created by digital technologies allow for substantial and spontaneous innovative input from large, uncoordinated audiences (i.e., generativity) and enable direct communication with other actors (i.e., disintermediation) (Autio et al., 2018). Generative digital technologies are dynamic and malleable (Yoo et al., 2012), while disintermediation facilitates knowledge and information exchange (Kwanya et al., 2015). Hence, by easing the experimentation and exploration of novel ideas and reducing the effort of collecting and transferring information, knowledge, and feedback, digital affordances provide support for innovative activities (Kankanhalli et al., 2015). Thus, digital affordances constitute a potential for gains of support resources (see Halbesleben et al., 2014).

Digital-technology-related support resources themselves also offer potentials for resource gains such as gains and savings of energy and time resources. For example, techno-support in the form of a facilitated collaboration and communication or an effortless retrieval of information and feedback eases and accelerates problem-solving (Day et al., 2010; Morgan et al., 2000). Moreover, these support resources could also manifest in the form of the provision of tangible digital technologies that offer the potential for gains and savings of time and energy resources reducing the resource investments necessary for intrapreneurial and innovative behavior. For example, support by collaborative technologies offers the potential to facilitate the sharing of knowledge and information and the exchange of ideas (Bélanger & Allport, 2008; Doll & Deng, 2001). Support by social media makes communication visible, allowing employees to more easily recombine existing ideas into new ones (Leonardi, 2014). Support by intelligent decision support

systems helps to screen, shift, and filter the increasing overflow of data, information, and knowledge in times of accelerating digitalization for effective and productive decision-making (Jantan et al., 2010). Furthermore, being provided with technologies that are characterized by a high usefulness and thus enable employees to accomplish tasks more quickly and increase their productivity (Davis, 1989) also holds the potential for resource gains in the form of time and energy resources. Due to this, employees may have more time and energy at their disposal that could be invested in acting outside of their formal roles, such as engaging in intrapreneurial and innovative activities.

However, digital technologies also offer the potential for resource losses, which could negatively affect the likelihood that employees will engage in behaviors that require significant resource investments themselves (Hobfoll, 1989, 2001) such as intrapreneurial and innovative activities. Generative digital technologies are characterized by high accessibility, increasing employees' connection to work by enabling them to work on job-related tasks at any time and from anywhere (Zittrain, 2007, 2008). Moreover, employees may feel inundated by the increased information inflow resulting from disintermediation and be forced to work faster to cope with the increased processing requirements (Ragu-Nathan et al., 2008). Therefore, on the one hand, digital affordances might result in employee-perceived work overload, which reflects a potential loss of energy resources (see Halbesleben et al., 2014). On the other hand, digital affordances may result in an unspoken value that appreciates employees to use digital technologies in order to be constantly available (Ayyagari et al., 2011). This could result in employees feeling that their private space has been invaded (see, e.g., Ayyagari et al., 2011; Gao et al., 2018; C. Lee et al., 2016). Hence, by contributing to this sense of privacy invasion, digital affordances offer the potential for the loss of constructive resources such as autonomy and control (see Halbesleben et al., 2014). Furthermore, techno-stressors such as information and communication overload may

result from improved communication and access to information (Day et al., 2010; Karr-Wisniewsky & Lu, 2010). Employees facing these types of overload have to invest energy and time resources to process the information, recover from interruptions, and think about and respond to incoming messages (Harris et al., 2015). This, in turn, leads to a forced reduction and consequent loss of resources. Additionally, the constant evolution of digital technologies and the expanding variety of associated functions compels employees to invest time and energy resources into learning and understanding how to use them (Tarafdar et al., 2011). Thus, having to work with complex digital technologies might also constitute a potential for resource losses.

Consequently, offering potentials for resource gains and losses, using digital technologies might be a double-edged sword regarding the two focal behavior types. Therefore, a resource perspective should help in exploring and examining how digital technologies foster and inhibit employee intrapreneurial and innovative behavior. Hence, the first research question is:

Research Question 1: What role do the potentials for resource gains and losses offered by the use of digital technologies play regarding employee intrapreneurial and innovative behavior?

As elaborated above, intrapreneurial behavior is fostered by individual and organizational factors (Blanka, 2019; Neessen et al., 2019). According to Hornsby et al. (1993), employee decisions to act intrapreneurially result from the interplay of a precipitating event that provides the impetus to perform intrapreneurial activities and organizational and individual characteristics. Support from digital technologies leads to gains and savings of time and energy resources and thus reduces the cost of performing intrapreneurial behaviors. Being provided with support by digital technologies might therefore represent both a potential for resource gains offered by the use of digital technologies and such a precipitating event. Hence, analyzing how organizational

and individual characteristics influence the relationship between digital technology support and employee intrapreneurial behavior may elucidate the conditions under which the potentials for resource gains offered by the use of digital technologies stimulate employees' intrapreneurial activities. Seen from a resource perspective, organizational and individual characteristics reflect organizational and personal resources. Following the logic of conservation of resources theory (Hobfoll, 1989, 2001), an individual's resource pool influences how situations are defined (e.g., as a threat or as an opportunity) (Ito & Brotheridge, 2003). People with more resources at their disposal are better positioned to invest resources and are shielded against resource loss (Hobfoll, 2001). Therefore, employees with stronger resource pools are more likely to define a situation as an opportunity. Hence, employees with more organizational and personal resources at their disposal might be more likely to perceive the opportunity to perform intrapreneurial activities at a lower cost due to the resource gains and savings offered by digital technology support. Thus, the precipitating effect of digital technology support should be stronger in that case. Therefore, the second research question is:

Research Question 2: How do additional organizational and personal resources moderate the relationship between digital technology support (as an example of the potentials for resource gains offered by the use of digital technologies) and employee intrapreneurial behavior?

Previous research has theorized employee innovative behavior to be largely a motivational issue (Amabile, 1988; Pieterse et al., 2010). Conservation of resources theory and the job demands-resources model are both theories of motivation and stress (Bakker & Demerouti, 2007, 2017; Hobfoll et al., 2018). According to those theories, saving and gaining resources and their presence have positive motivational consequences because this makes it

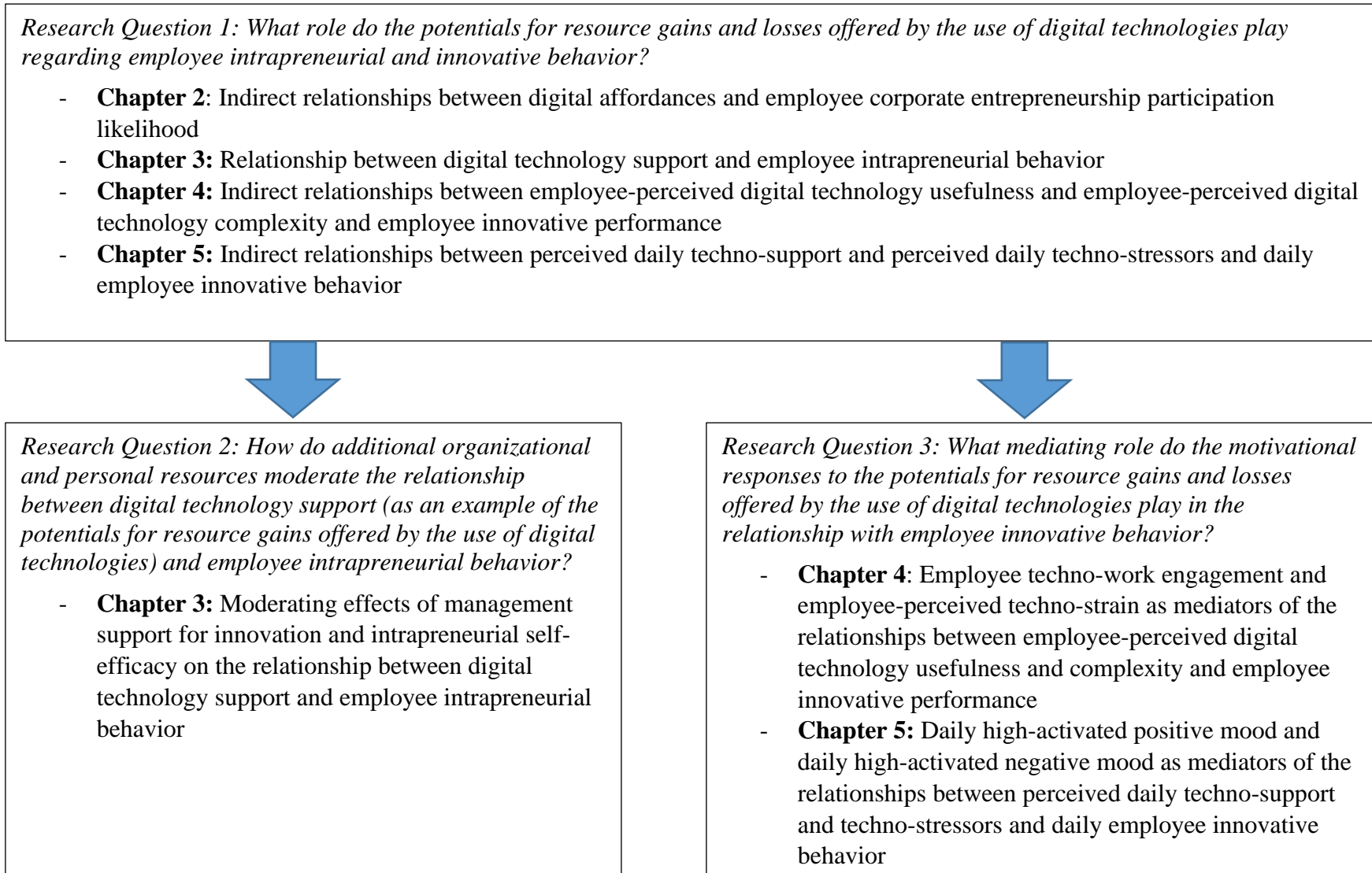
easier for individuals to gain additional resources and to preserve their current resource pool, which are two fundamental human goals (Halbesleben et al., 2014; Hobfoll, 1989, 2001; Hobfoll et al., 2018). Consequently, having the opportunity to work with digital technologies that offer the potential for saving and gaining resources should have positive motivational effects.

Employees being able to meet the fundamental goal of increasing and preserving their resource pool might lead to high-activated positive affective responses (Madrid & Patterson, 2020). These affective motivational factors influence proactive behaviors such as employee innovative endeavors (Bindl et al., 2012). Potentials for resource gains in the form of digital-technology-related job resources such as useful digital technologies could lead to the motivational state of employee work engagement (Bakker & Demerouti, 2007, 2017), which also potentially drives innovative behavior (e.g., Chang et al., 2013).

However, individuals fear losing resources and tend to withdraw from actions that might ultimately threaten their resource pool (Halbesleben et al., 2014; Hobfoll, 1989, 2001). Thus, the potentials for resource losses associated with the use of digital technologies could also entail adverse motivational consequences. The fear of potential resource losses (Halbesleben et al., 2014; Hobfoll, 1989, 2001) might result in high-activated negative affective responses, which could trigger employees to actively withdraw from work to protect their well-being (Carver & White, 1994). Furthermore, resource losses caused by the use of digital technologies might also lead to strain (Ayyagari et al., 2011; Maier et al., 2015) with negative motivational consequences (Bakker et al., 2004). Accordingly, the third research question is:

Research Question 3: What mediating role do the motivational responses to the potentials for resource gains and losses offered by the use of digital technologies play in the relationship with employee innovative behavior?

Figure 1 provides an overview of this thesis' research questions and shows how they are addressed in each of the remaining chapters.

Figure 1*Overview of the Dissertation*

1.3 Structure of the Work

Chapter 2 is co-authored by Prof. Dr. Tanja Rabl and Prof. Dr. Matthias Baum. It sets out a scenario-based experimental study with 207 employees working full-time in for-profit organizations in Germany. The study examines the mediating mechanisms in the relationship between digital affordances (i.e., generativity and disintermediation) and employee corporate entrepreneurship participation likelihood. Based on the conservation of resources theory (Hobfoll, 1989, 2001), it proposes resource gains in the form of employee-perceived IT support for innovation and resource losses in the form of employee-perceived work overload and invasion of privacy as mediators. This chapter contributes to knowledge on the drivers of employee corporate entrepreneurial activities by introducing digital affordances as important determinants of employee corporate entrepreneurship participation likelihood. It also introduces an employee perspective on digital affordances by examining these as antecedents of employee behavior and analyzing the resource gains and losses for the individual employee stemming from those digital affordances. It also helps to disentangle the potentially adverse mechanisms fostered by digital affordances regarding employee corporate entrepreneurial activities. Moreover, the chapter makes an additional important theoretical contribution by introducing conservation of resources theory (Hobfoll, 1989, 2001) as a stress and motivation theory (Halbesleben et al., 2014; Hobfoll, 2001; Hobfoll et al., 2018) into the realm of employee corporate entrepreneurship participation likelihood. The findings here may help practitioners to better understand the mediating mechanisms in the relationship between digital affordances and employee corporate entrepreneurship participation likelihood. This knowledge allows practitioners to design a digital-technology infrastructure that fosters employee willingness to engage in corporate entrepreneurial activities.

Also co-authored by Prof. Dr. Tanja Rabl and Prof. Dr. Matthias Baum, Chapter 3 presents a metric conjoint experiment with 1,360 decisions nested within 85 employees working full-time in for-profit organizations in the manufacturing sector in Germany. Drawing on the model of the corporate entrepreneurship process (Hornsby et al., 1993) and conservation of resources theory (Hobfoll, 1989, 2001), it investigates the relationship between support by three types of digital technologies (support by collaborative technologies, support by social media, and support by intelligent decision support systems) and employee intrapreneurial behavior. It also examines the moderating effects of management support for innovation as an organizational resource and intrapreneurial self-efficacy as a personal resource. In doing so, this chapter extends the digital entrepreneurship literature, which has, to date, been largely conceptual. By considering both organizational and individual characteristics as contingencies, the study offers valuable clues as to the circumstances in which digital technology support enables employee intrapreneurial behavior. With this, we add to the theorizing of von Briel et al. (2018) on digital technologies as enablers of entrepreneurial processes and provide further insights into the interaction of personal and organizational resources and their role in the decision to act intrapreneurially. This helps practitioners to understand which organizational and individual factors leverage the potential of digital technology support to promote intrapreneurial employee behavior.

Chapter 4 is single-authored and sets out a three-phase online survey study with 162 employees working in for-profit organizations in Germany. The study examines the mediating mechanisms in the relationships between the digital technology characteristics employee-perceived digital technology usefulness and employee-perceived digital technology complexity on the one hand and employee innovative performance on the other hand. Based on the job demands-resources model (Bakker & Demerouti, 2007, 2017; Demerouti et al., 2001), this

chapter proposes employee techno-work engagement and employee-perceived techno-strain as mediators. In doing so, Chapter 4 answers the call by Nambisan et al. (2017) to closer investigate the role of digital technologies and infrastructures in innovative processes and how they enable and constrain innovative activities. It also contributes to knowledge on the determinants and outcomes of employee techno-work engagement, a novel construct based on general work engagement (Mäkinen et al., 2020). This study extends the job demands-resources model literature by introducing employee-perceived digital technology usefulness and complexity as digital-technology-related job resources and demands, respectively, and analyzing their relationship with employee innovative performance. For practitioners, it provides insights and guidance on how to design their organization's digital-technology infrastructure to be conducive, rather than detrimental, to employees' innovative performance.

Previous studies found that employee innovative behavior fluctuates between days (e.g., Madrid et al., 2014; Williamson et al., 2019). Chapter 5, which is co-authored by Prof. Dr. Tanja Rabl, presents a diary study with two daily surveys over the course of ten workdays with 1,727 data points nested in 94 employees that worked full-time. It draws on affective events theory (Weiss & Cropanzano, 1996) and conservation of resources theory (Hobfoll, 1989, 2001) to examine the relationships of perceived daily techno-support (i.e., perceived daily support for communication and collaboration and perceived daily ease of effort) and perceived daily techno-stressors (i.e., perceived daily information overload and perceived daily communication overload) with daily employee innovative behavior. It also explores the mediating role of daily high-activated positive mood and daily high-activated negative mood. By analyzing daily employee innovative behavior, we answer the call by Orth and Volmer (2017) for more research that investigates employee innovative activities within individuals and shed more light on why innovative behavior of the same employee differs between days (Breevaart & Zacher, 2019). To

our knowledge, this is the first study that theorizes and empirically tests perceived daily techno-support and perceived daily techno-stressors as antecedents of daily employee innovative behavior. As such, we also contribute to research on digital technologies and digital innovation. Furthermore, we provide guidance for practitioners on how to promote innovative behavior on specific days when it might be particularly important to be innovative.

Chapter 6 provides the overall summary of this thesis and elaborates on implications for theory and practice. Furthermore, it illustrates limitations of the thesis and offers avenues for future research. Finally, Chapter 7 presents the thesis' conclusion.

2. Perceived Resource Gain or Loss? How Digital Affordances Influence Employee Corporate Entrepreneurship Participation Likelihood

2.1 Abstract

Based on conservation of resources theory, this chapter examines the mediating mechanisms in the relationship between digital affordances and employee corporate entrepreneurship participation likelihood. It sets out findings from an experimental study with 207 employees working full-time in for-profit organizations in Germany and shows a statistically significant and positive indirect effect of digital affordances on employee corporate entrepreneurship participation likelihood via employee-perceived IT support for innovation and – contrary to our expectations – a statistically significant and positive indirect effect via employee-perceived work overload. Results provide support for digital affordances as action potentials that are associated with resource gains that, in turn, increase employee corporate entrepreneurship participation likelihood.

Keywords: conservation of resources theory; corporate entrepreneurship; digital affordances; invasion of privacy; IT support for innovation; work overload

2.2 Introduction

Corporate entrepreneurship is “the process whereby an individual or group of individuals, in association with an existing organization, create a new organization or instigate renewal or innovation within that organization” (Sharma & Chrisman, 1999, p. 18). This process breeds organizational rejuvenation and competitive advantage that allows organizations to adequately respond to dynamic and uncertain environments and secure their long-term competitiveness (Mahdjour & Fischer, 2014). The burgeoning literature on digital entrepreneurship has recently begun to argue that digital affordances enhance entrepreneurial activities (Autio et al., 2018; Nambisan, 2017; von Briel et al., 2018). *Digital affordances* refer to action potentials of digital technologies in terms of “what an individual or organization with a particular purpose can do with a technology or information system” (Majchrzak & Markus, 2013, p. 832). By allowing existing organizations to invent new methods to create, deliver, and capture value (Autio et al., 2018; Prahalad & Ramaswamy, 2003), digital affordances may also act as drivers for corporate entrepreneurial activities. For instance, digital technologies allow for substantial and spontaneous innovative input from large, uncoordinated audiences (i.e., generativity) and enable direct communication with end-users, which provides flexibility gains and new business opportunities (i.e., disintermediation) (Autio et al., 2018). As digital affordances such as generativity and disintermediation support radical business-model innovation, they have a transformative effect on the organization of economic activity and provide new potential for value creation (Autio et al., 2018; Nambisan et al., 2017).

Given the key role of employees and their participation in the success of corporate entrepreneurial projects (Hornsby et al., 2002; Monsen et al., 2010), it is important to take an employee perspective both on corporate entrepreneurship and on digital affordances. However,

doing so provides a more complex picture. Previous research on digital technologies suggests that digital affordances may be a double-edged sword (see, for example, S. Chen et al., 2009; Diaz et al., 2012) regarding how they affect employee extra-role performance such as corporate entrepreneurial behavior. On the one hand, digital affordances may enhance employee corporate entrepreneurship participation likelihood by providing opportunities to experiment with new ideas and facilitating interactions with multiple stakeholders (Autio et al., 2018). On the other hand, employees may anticipate that the installment of digital technologies brings with it an increased workload, or they may fear an invasion of privacy, which may cause stress (Ayyagari et al., 2011; Ragu-Nathan et al., 2008). These factors may reduce their motivation to participate in demanding innovative, proactive, and risky endeavors such as corporate entrepreneurship projects. This study takes a deeper look at this potentially double-edged sword. It examines how and why the affordances associated with digital technologies in an organization influence the likelihood of employees to participate in a corporate entrepreneurship project.

We aim to provide the following contributions. First, scholars' understanding of how the internal corporate environment affects employee corporate entrepreneurial behavior is still far from complete (Rigtering et al., 2019). Further research is thus needed on how employee corporate entrepreneurial intentions can be fostered (Kuratko, Hornsby, & Hayton, 2015). Researchers have already examined the role in fostering corporate entrepreneurial activities of supportive management, organizational structures, and climate; rewards; work autonomy; and availability of time and financial resources (Neessen et al., 2019). Additionally, Y. Chen et al. (2015) found a positive relationship between an organization's IT capabilities and organization-level corporate entrepreneurship. However, in order to successfully establish corporate entrepreneurship projects, organizations need to know how individuals react when provided with digital-technology resources – a research stream that remains largely understudied. Hence, our

study improves our knowledge of the drivers of employee corporate entrepreneurial activities by introducing digital affordances, a concept originally rooted in the entrepreneurship (Autio et al., 2018) and innovation management research (Nambisan et al., 2017), as important determinants of employee corporate entrepreneurship participation likelihood. In doing so, we also introduce an employee perspective on digital affordances.

Second, our study helps to disentangle the potentially adverse mechanisms fostered by digital affordances regarding employee corporate entrepreneurial activities. We build and empirically test theory to resolve the puzzle about potential fostering and hindering influences of digital affordances on employee corporate entrepreneurship participation likelihood. As research on digital affordances is still in its infancy and has mainly been conceptual, our study is one of the first to empirically examine digital affordances. It links these with corporate entrepreneurship and thus contributes to research on both corporate entrepreneurship and digital affordances. In addition, our study provides evidence-based insights on digital entrepreneurship— a still-emerging field of research that is so far also largely conceptual in nature (see, e.g., Autio et al., 2018; Nambisan, 2017).

Third, our study makes an important theoretical contribution by introducing conservation of resources theory (Hobfoll, 1989, 2001), a stress and motivation theory (Halbesleben et al., 2014; Hobfoll, 2001; Hobfoll et al., 2018) into the realm of employee corporate entrepreneurship. We elaborate on the individual-level processes reflecting the resource gains and losses associated with digital affordances that potentially foster or hinder employee corporate entrepreneurship participation likelihood. In so doing, we add to the literatures on corporate entrepreneurship and the conservation of resources theory. Unlike the theories commonly used to explain individual decisions to act entrepreneurially, such as the theory of planned behavior or the model of the entrepreneurial event (Krueger et al., 2000), conservation of resources theory addresses the

effects of resource gains and losses on an individual's behavioral decision-making and can thus capture the potentially double-edged nature of digital affordances regarding employee corporate entrepreneurship participation likelihood (Hobfoll, 2001, Hobfoll et al. 2018).

2.3 Theory and Hypotheses

2.3.1 Digital Affordances and Employee Corporate Entrepreneurship Participation

Likelihood: A Resource Perspective

Digitalization introduces affordances such as generativity and disintermediation (Autio et al., 2018).¹ *Generativity* is the ability of digital technologies to facilitate unprompted innovative input from large, diverse, and uncoordinated audiences (Zittrain, 2006). Generative digital technologies are dynamic and malleable (Yoo et al., 2010), which increases the unpredictability and fluidity of entrepreneurial outcomes (Autio et al., 2018). Generativity is characterized by four main features: leverage, adaptability, ease of mastery, and accessibility. Leverage is the capacity of digital technologies to produce an output that is disproportionately greater than the input. Adaptability reflects the ease with which digital technologies can be modified to broaden the range of their functionalities. Ease of mastery refers to how easy it is for people to both adopt and use digital technology. Accessibility describes how easily people can obtain the information necessary for mastering a digital technology and the more readily they can come to use and control it (Zittrain, 2006, 2007).

¹ Additionally, digitalization drives the de-coupling between the form and function of assets. De-coupling results directly from the bit structure of digital technologies (Autio et al., 2018). In contrast to generativity or disintermediation, it is a common feature to all types of digital technologies (von Briel et al., 2018; Yoo et al., 2010). As there is no variance in the extent of de-coupling across different digital technologies, we do not consider it in this study.

Disintermediation describes the ability of digital technologies to support direct interactions between two individuals so that intermediaries are no longer needed (Autio et al., 2018; Bakos, 1998; Gellman, 1996; Jallat & Capek, 2001). It results from the possibility of directly and seamlessly communicating with end-users (Autio et al., 2018; P. B. Evans & Wurster, 1997). Allowing the interacting parties to handle a wider range of interactions at lower costs (Crowston & Myers, 2004), disintermediation makes interactions cheaper. Having immediate access to the required information, organizational members no longer have to rely on stationary intermediaries as sources of information to coordinate the progress of locally dispersed projects (Gellman, 1996). Furthermore, disintermediation facilitates the flexible configuration and coordination of teams by allowing the direct exchange of information regardless of one's location (Autio et al., 2018).

Drawing on conservation of resources theory (Hobfoll, 1989, 2001), we explore these digital affordances as a potentially double-edged sword. We examine from a resource perspective the relationship between generativity and disintermediation on the one hand and employee corporate entrepreneurship participation likelihood on the other. *Resources* are “those objects, personal characteristics, conditions, or energies that are valued by the individual or that serve as a means for the attainment of these objects, personal characteristics, conditions, or energies” (Hobfoll, 1989, p. 516). They are “anything perceived by the individual to help attain his or her goals” (Halbesleben et al., 2014, p. 1338). According to conservation of resources theory (Hobfoll, 1989, 2001), individuals are likely to engage in corporate entrepreneurial behavior when they expect a net gain of resources; that is, when they expect that the behavior is associated with more resource gains than resource losses. The problem is that for the individual employee, engagement in corporate entrepreneurial activities incorporates both potential resource gains and losses (Gawke et al., 2017, 2018). Employee corporate entrepreneurship behaviors can activate

self-efficacy (Bandura, 1997), optimism (Carver & Scheier, 2002), and resilience (Masten, 2001) by allowing employees to experience success, achieve action goals, and master challenges (Gawke et al., 2017). Additionally, employee engagement in corporate entrepreneurial activities might result in financial resource gains (e.g., via profit sharing; Monsen et al., 2010). However, the engagement in corporate entrepreneurial activities also requires the investment of resources (Gawke et al., 2018), such as additional energy and time (Scott & Bruce, 1994) as well as personal resources (e.g., optimism, self-efficacy, and resilience; Gawke et al., 2017) to deal with risk and uncertainty (McGrath, 1999; McGrath & MacMillan, 2000).

Which side prevails is a function of organizational resources and the extent to which they enhance the likelihood of a net gain rather than a net loss of resources. The underlying processes reflect the potential for resource accumulation and resource conservation (Ng & Feldman, 2012) as proposed by conservation of resources theory (Hobfoll, 1989, 2001). The resource accumulation argument postulates that individuals strive to obtain new resources. When employees acquire new resources, they are shielded from resource loss and become capable of additional resource gains; their resources can be invested to acquire further resources (Halbesleben et al., 2014; Hobfoll, 2001). According to the resource conservation argument, individuals experiencing resource loss engage less in behaviors that consume additional resources and adopt a defensive posture to conserve their remaining resources (Halbesleben et al., 2014; Hobfoll, 2001; Hobfoll et al., 2018). We argue that the affordances of digital technologies are organizational resources that carry the potential of both resource gains and losses and thus influence employee corporate entrepreneurship participation likelihood.

Previous research has identified various forms of resources as important to fostering employee corporate entrepreneurial activities or related behavior types such as innovative work behavior. These include support resources (Hornsby et al., 2002, 2009), energy resources (de

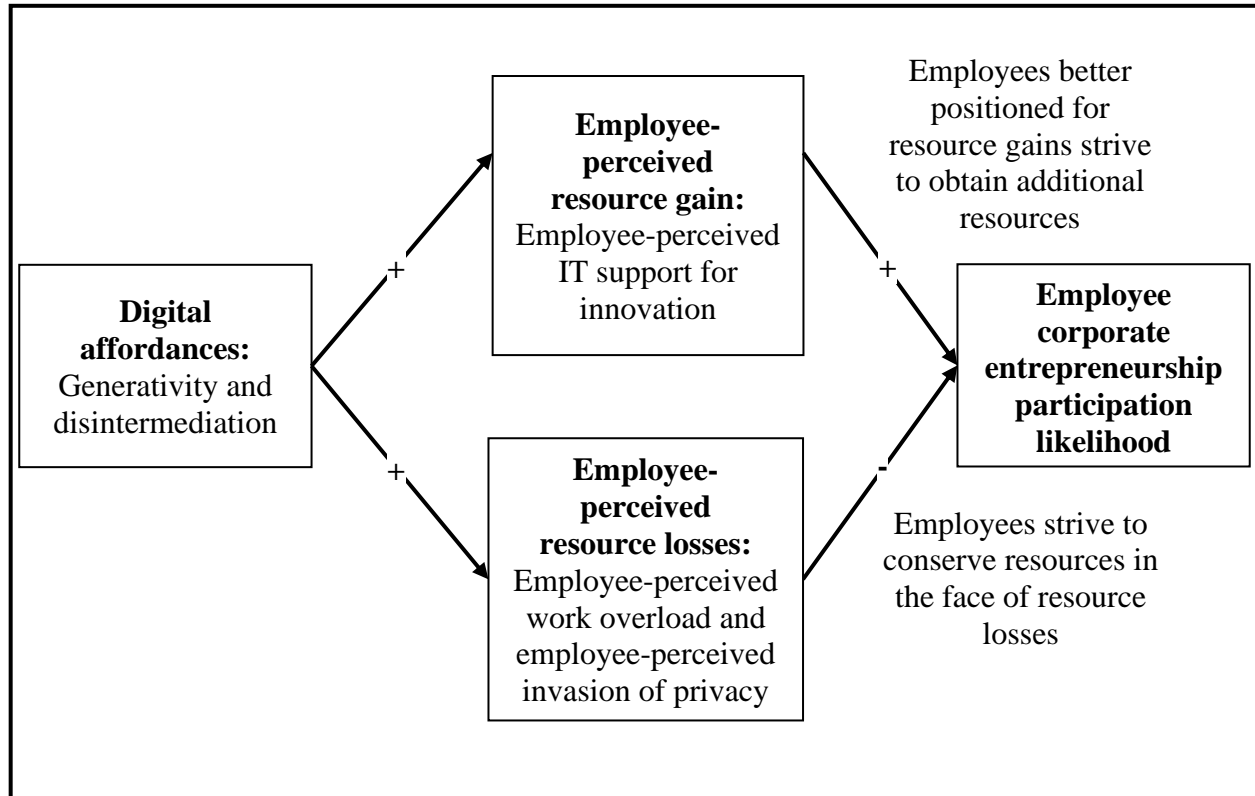
Clercq et al., 2016; Weinberger et al., 2018; Williamson et al., 2019), autonomy resources (de Spiegelaere et al., 2014; Hornsby et al., 2002, 2009), control resources (de Clercq et al., 2018; Janssen, 2000), and fairness resources (Janssen, 2004; Moon et al., 2008).

By enabling the exploration of ideas and reducing the effort of collecting and transferring information and feedback, digital affordances support innovative activities (Dodgson et al., 2002; Kankanhalli et al., 2015). Hence, employee-perceived IT support for innovation is likely to reflect a perceived gain of support resources associated with digital affordances and allows for resource accumulation (see Halbesleben et al., 2014).

However, by increasing information inflow, digital affordances might make employees feel that their capacities are exceeded (see, e.g., Ahuja et al., 2007; Ayyagari et al., 2011; Turel et al., 2011). This perceived work overload means a perceived loss of energy resources (Halbesleben et al., 2014) that triggers resource conservation. Moreover, by blurring the boundaries between work and home, digital affordances might result in employees seeing their privacy as compromised (see, e.g., Ayyagari et al., 2011; Gao et al., 2018; C. Lee et al., 2016). This perceived invasion of privacy means not only a perceived loss of constructive resources such as autonomy and control (see Halbesleben et al., 2014) but also a perceived loss of the job resource procedural fairness (e.g., Boyd et al., 2011). Therefore, a perceived invasion of privacy is likely to also reflect a perceived resource loss that is induced by digital affordances and fosters resource conservation. Figure 2 shows our theoretical rationale based on conservation of resources theory. We explain the proposed processes in detail in the sections that follow.

Figure 2

Theoretical Rationale: Mediating Mechanisms Between Digital Affordances and Employee Corporate Entrepreneurship Participation Likelihood



2.3.2 Employee-Perceived IT Support for Innovation as a Mediator Between Digital Affordances and Employee Corporate Entrepreneurship Participation Likelihood

We posit that digital affordances may lead to perceptions of resource gains in the form of *employee-perceived IT support for innovation*. This indicates the extent to which employees perceive digital technologies as supporting their innovative behavior by reducing effort and facilitating exploration (Kankanhalli et al., 2015). Correspondingly, employee-perceived IT support for innovation consists of two sub-dimensions: employee-perceived exploration and employee-perceived ease of effort. *Employee-perceived exploration* refers to the extent to which a digital technology facilitates the development of, experimentation with, and exploration of

ideas. *Employee-perceived ease of effort* reflects the extent to which a digital technology reduces the effort of innovating (Kankanhalli et al., 2015; Ye & Kankanhalli, 2018).

Generativity is likely to foster resource gains in the form of employee-perceived IT support for innovation. By offering the possibility of contributing to an innovative project at any time and place (Autio et al., 2018), generative digital technologies reduce the effort employees need to invest in innovating. Generativity allows all employees and external partners to co-create content and thus supports the combination of any information in the network (Tilson et al., 2010). By being malleable, reprogrammable, and therefore easily adaptable (Yoo et al., 2010), generative technologies should facilitate the trial of and experimentation with new ideas. Disintermediation is also likely to enhance resource gains in the form of employee-perceived IT support for innovation. By allowing direct communication (Autio et al., 2018) that facilitates knowledge and information exchange (Kwanya et al., 2015), disintermediation reduces the effort necessary for creating innovations. As it enables the direct and unfiltered receipt of feedback and advice (Autio et al., 2018), disintermediation can foster experimentation with new ideas.

According to the resource accumulation argument of conservation of resources theory (Hobfoll, 1989, 2001), employees perceiving resource gains in the form of IT support for innovation feel in a better position to invest these resources and gain additional resources by engaging in corporate entrepreneurial activities. Employee-perceived IT support for innovation lowers the psychological costs associated with corporate entrepreneurial behavior by reducing the fear of failure of a corporate entrepreneurial activity. This is because IT support for innovation helps employees identify if ideas are worth pursuing (Kankanhalli et al., 2015). Moreover, by facilitating the acquisition of information, knowledge, and feedback, IT support also decreases the amount of effort and time that needs to be invested in the corporate entrepreneurial activity (Ye & Kankanhalli, 2018). Accordingly, employee-perceived IT support for innovation should result in

employees expecting a net gain of resources when engaging in such behavior. This support should therefore foster employee corporate entrepreneurship participation likelihood. Thus, we propose:

Hypothesis 1: Employee-perceived IT support for innovation positively mediates the relationship between a) generativity and b) disintermediation and employee corporate entrepreneurship participation likelihood.

2.3.3 Employee-Perceived Work Overload as a Mediator Between Digital Affordances and Employee Corporate Entrepreneurship Participation Likelihood

Digital affordances can also potentially lead to resource losses. As stated above and based on discussions in the literature (e.g., Ahuja et al., 2007; Ayyagari et al., 2011; Turel et al., 2011), *employee-perceived work overload*, the extent to which employees feel that the assigned work exceeds their capacity or skill levels (Ayyagari et al., 2011; Cooper et al., 2001; J. E. Moore, 2000), is a possible perceived resource loss associated with digital affordances.

As generative digital technologies are characterized by high accessibility, generativity increases the connection between employees and their work by enabling employees to work on job-related tasks anytime and from anywhere (Zittrain, 2007, 2008). Furthermore, although generativity facilitates the retrieval of ideas, information, and feedback, getting unfiltered input from large, uncoordinated audiences might quickly cause information overload (Remneland-Wikhamn et al., 2011). Disintermediation allows for direct and seamless interactions with other project participants (Autio et al., 2018). Such advances in connectivity allow employees to send and receive work-related messages at any time (Barley et al., 2011). Employees may feel inundated by the increased information inflow and feel forced to work faster to cope with the increased processing requirements (Ragu-Nathan et al., 2008). The resulting increase in time pressure at work (Ayyagari et al., 2011) has been identified as an antecedent of work overload

(Cooper et al., 2001; Narayanan et al., 1999). Employees may feel the pressure of having to answer immediately, even without an explicit demand for timely communication (Barley et al., 2011). This constant engagement in work-related tasks may cause a feeling of work overload (Turel et al., 2011). Consequently, generativity and disintermediation are likely to lead to an increased information inflow and an acceleration of the pace of work, which may result in perceptions of resource loss (S. Chen et al., 2009).

According to the resource conservation argument of conservation of resources theory (Hobfoll, 1989, 2001), employees perceiving work overload and therefore lacking energy and time for private activities should be less willing to invest additional time and energy to perform potentially resource-consuming behaviors such as corporate entrepreneurship (de Clercq et al., 2016). This is consistent with the results of Ng and Feldman's (2012) meta-analysis, which found a negative relationship between employees facing job stressors such as dissatisfaction with work conditions (and thus perceiving resource loss) and the willingness of those employees to perform extra-role behaviors. This also corresponds with work by Hornsby et al. (1993) that proposes that a lack of time resources is detrimental to employee willingness to engage in corporate entrepreneurial activities. Accordingly, employee-perceived work overload should result in employees expecting a net loss of resources when engaging in corporate entrepreneurial activities, and therefore decrease employee corporate entrepreneurship participation likelihood. Thus, we propose:

Hypothesis 2: Employee-perceived work overload negatively mediates the relationship between a) generativity and b) disintermediation and employee corporate entrepreneurship participation likelihood.

2.3.4 Employee-Perceived Invasion of Privacy as a Mediator Between Digital Affordances and Employee Corporate Entrepreneurship Participation Likelihood

As argued above and based on discussions in the literature (e.g., Ayyagari et al., 2011; Gao et al., 2018; C. Lee et al., 2016), *employee-perceived invasion of privacy*, the extent to which employees see their privacy being compromised through the use of digital technology (Ayyagari et al., 2011), is likely to reflect another form of perceived resource loss instigated by digital affordances. Digital technologies characterized by high generativity and disintermediation allow employee privacy to be compromised and private life to become invaded by work-related issues. Generativity brings along the possibility to contribute to work progress anytime and from anywhere (Autio et al., 2018; Zittrain, 2007, 2008), and disintermediation enables direct communication (Autio et al., 2018). Digital affordances may thus result in an unspoken valuing of employees using digital technologies to be constantly available (Ayyagari et al., 2011). This continuous exposure might make employees feel that they are always under supervision or on-call (Tarafdar et al., 2010), that their private time and space have been invaded (Ragu-Nathan et al., 2008), and that they have less private time (Tu et al., 2005).

In addition, digital technologies characterized by high generativity and disintermediation also raise concerns regarding information privacy because they are able to monitor and track employee activities using digital technologies (C. Lee et al., 2016). Consequently, employees fear the disclosure and misuse of private information (Gao et al., 2018). As a result of the perceived monitoring, they feel a loss of control over the information disclosed to the organization (Fusilier & Hoyer, 1980; Lei & Ngai, 2014). Lacking control over what and to whom personal information is disclosed has been found to reduce the perception of procedural fairness and increase the perception that privacy has been invaded (Eddy et al., 1999).

According to the resource conservation argument of conservation of resources theory (Hobfoll, 1989, 2001), employees perceiving the loss of private time, control over personal information disclosure, and procedural fairness will want to conserve the resources that remain and will be reluctant to invest additional resources to engage in corporate entrepreneurship. This is underlined by previous research showing that resource losses with regard to control (Niehoff & Moorman, 1993) and procedural fairness (Moorman et al., 1993) negatively affect extra-role behaviors. The authors of these studies argue that such resource losses decrease employee faith and trust (Organ, 1988). Similarly, research indicates low levels of autonomy resources have a negative effect on employee willingness to perform extra-role behaviors (Parker et al., 2006; Zhang & Chen, 2013). Corporate entrepreneurial activities require employees to invest additional time and energy resources (Scott & Bruce, 1994) but also personal resources such as optimism, self-efficacy, and resilience (Gawke et al., 2017) to deal with risk and uncertainty (McGrath, 1999; McGrath & MacMillan, 2000). Employees perceiving an invasion of privacy through digital technologies characterized by high generativity and high disintermediation will strive to conserve rather than invest their remaining resources to avoid the net loss that might result from engaging in corporate entrepreneurial activities. Hence, an employee-perceived invasion of privacy should decrease employee corporate entrepreneurship participation likelihood. Thus, we propose:

Hypothesis 3: Employee-perceived invasion of privacy negatively mediates the relationship between a) generativity and b) disintermediation and employee corporate entrepreneurship participation likelihood.

2.4 Method

2.4.1 Sample

To empirically test our hypotheses using a between-subject experimental design, we recruited employees from different age groups who matched our inclusion criteria. To meet those criteria, potential participants had to work full-time in for-profit organizations in Germany, needed to have managerial tasks, and had to work in settings and positions in which they might realistically be asked if they are willing to join a corporate entrepreneurship project.

First, to achieve a heterogeneous sample and to increase the generalizability of our findings (Demerouti & Rispens, 2014), a student-researcher team assisted in compiling a list of 722 potentially suitable study participants from their professional and social networks (for a similar approach, see, e.g., Diebig et al., 2016; Petrou & Bakker, 2016). In a second step, we invited a random subset of 80% of that pool (i.e., 577 employees) to participate in our study with an e-mail including the link to the study questionnaire. Participants were randomly assigned to the different experimental conditions resulting in an approximately equal distribution. To ensure the quality of our data, we followed Demerouti and Rispens' (2014) advice and instructed the student-researcher team on experiments, sampling techniques, and biases. Additionally, we checked our inclusion criteria via corresponding questions included in the survey. In total, 231 participants provided complete answers and passed the check for inclusion criteria, which reflects a response rate of 40.03%. However, we had to exclude 24 participants who did not consider the scenario to be realistic, which results in a final sample of 207 participants.

In this final sample, 20.19% of respondents were female. A total of 7.25% had a migration background. On average, the respondents were 36.91 years old ($SD = 11.06$; $MIN = 22$ years; $MAX = 62$ years) and had 14.03 years of work experience ($SD = 11.81$; $MIN < 6$ months;

MAX = 42 years). In our sample, 65.22% held a university (or comparable) degree, and 3.38% had a Ph.D. Most respondents (73.91%) worked in organizations with 250 or more employees. Additionally, participants were employed in various industries. Among participants, 48.31% had a leadership position in their organization. Regarding their level in the hierarchy, 33.33% held operational positions, 42.51% lower-management positions, 18.36% middle-management positions, 4.83% upper-management positions, and 0.97% top-management positions.² According to Hornsby et al. (2009), actors at different hierarchical levels – ranging from operational level employees to top managers – are involved in corporate entrepreneurship activities. Thus, our sample includes realistic targets for corporate entrepreneurial engagement (Baum & Rabl, 2019; Jessri et al., 2020; Monsen et al., 2010).

2.4.2 Study Design and Procedures

We conducted an experimental study that used a two-by-two (2x2) between-participant design and manipulated two factors: generativity (high versus low) and disintermediation (strong versus weak). A scenario-based experimental design is particularly suitable for examining employee participation in corporate entrepreneurial activities. It ensures a high level of internal validity and delivers results that accurately reflect the real-world decision-making behavior of individuals (Aguinis & Bradley, 2014; Brown, 1972; K. R. Hammond & Adelman, 1976).

Each respondent was confronted with a hypothetical scenario describing one of the four experimental conditions. We made sure that the project described in our scenarios reflected the innovative, proactive, and risky nature of a new corporate venture (Miller, 1983). In doing so, we followed previous studies examining employee willingness to participate in corporate entrepreneurial activities (e.g., Monsen et al., 2010). Thus, scenarios started with instructing

² Holding a management position does not necessarily correspond with having a leadership function (Yukl, 2013).

respondents to imagine their organizations ask if they want to participate in a new, innovative project that requires their particular expertise and ability and is conducted in collaboration with external partners. Respondents were told they needed to react quickly and sign a new working contract to be able to participate in the project. These two conditions were integrated to represent the innovative and proactive characteristics of a new corporate venture. Additionally, the scenario emphasized that a project failure could have negative consequences for the employee's career, which reflected the risky element of an entrepreneurial project. To account for the structural dimensions of a new corporate venture, respondents were told that, if successful, the project might result in a new strategic business unit or an independent spin-off (Sharma & Chrisman, 1999). To facilitate immersion and thus further improve the external validity of our scenarios (Aguinis & Bradley, 2014), participants were asked to consider the project under their organization's current conditions and to assume that, except for the cloud-based software solution described in the scenario, the hypothetical project's type and scope would be comparable to current or previous projects in their organization.

Following the scenario introduction, each participant was confronted with one of the four experimental conditions. These were presented as one of four different descriptions of the cloud-based software used to support the hypothetical project. Based on the scenario presented, participants had to respond to our measures of the mediator and dependent variables. In the survey, they also provided information on socio-demographics and control variables. Combining a scenario-based experimental design with a survey enhanced the external validity of our study (Atzmüller & Steiner, 2010).

The generativity manipulation was based on the conceptualization of generativity and its four main features: leverage, adaptability, ease of mastery, and accessibility (Zittrain, 2006, 2007). In the high-generativity condition, the project's cloud-based software was activated for all

project participants enabling them to spontaneously contribute to the project's progress regardless of their location (high accessibility). The software could be easily adapted and reprogrammed (high adaptability) and used without a long period of training (high ease of mastery). It allowed the combination with all other common programs and an integration with the software used by departments and partners not currently involved in the project (high leverage). In the low-generativity condition, the cloud-based software used in the project was only activated for a limited number of project participants enabling only a small number of people to spontaneously contribute to the project's progress regardless of their current location. The software access was limited to the stationary computer in the respondent's office (low accessibility). Any adaption and reprogramming would be greatly time-consuming (low adaptability), and the software could only be used after a long phase of intensive training (low ease of mastery). Additionally, the combination with other common programs or an integration with the software used by departments and partners not currently involved in the project would be difficult (low leverage).

The manipulation of disintermediation was created based on the description in Autio et al. (2018). In the strong-disintermediation condition, the cloud-based software allowed direct interaction between all project participants so that immediate communication was possible. It allowed access to the databases of all departments and partners involved in the project for direct retrieval of the required information. Moreover, a feedback tool included in the software enabled a direct feedback on the propositions and drafts of other project participants. In the weak-disintermediation condition, the cloud-based software did not allow direct interaction between the participants so that all communication between participants had to be gathered and transferred by the project coordinator. It was also necessary to contact the project coordinator to receive the information needed from departments and partners involved in the project. In addition, the

software included only a poor feedback tool; feedback had to be directed to the project coordination.

We conducted a pretest with 47 employees fulfilling our inclusion criteria using online questionnaires and following a between-participant design. This allowed us to increase the study's external validity, ensure the content validity of the scenarios, and check the generativity and disintermediation manipulations (Hsu et al., 2017). After having completed the online questionnaire, the pretest participants were asked whether they understood the scenario and the questions, if they had any problems in completing the study, and if they perceived the presented scenario to be realistic. Besides slight adjustments to our scenarios and manipulation-check items to increase understandability, we kept the design for our main study.

2.4.3 Manipulation Check

To check the manipulation of generativity in our main study, respondents were asked to judge the perceived generativity of the cloud-based software solution on a five-point Likert-type scale (1=*does not apply at all* to 5 = *fully applies*) in response to the statements, "This software allows unprompted innovative input from all project participants," and "This software enables all project participants to spontaneously and innovatively contribute to the project." To check the manipulation of disintermediation, we asked for participants' judgment regarding perceived disintermediation. We asked them to rate the statements, "The software allows to directly and seamlessly communicate with other project participants without being dependent on project coordinators," and "The software supports direct interactions between all project participants without having to fall back on project coordinators," on a five-point Likert-type scale (1 = *does not apply at all* to 5 = *fully applies*). We conducted *t*-tests on the manipulation-check measures, which showed a statistically significant difference ($t = -6.94, p < .01$) between the low- ($\bar{x} = 2.81$,

$SD = 1.12$) and the high-generativity condition ($\bar{x} = 3.77$, $SD = 0.84$) and a statistically significant difference ($t = -11.85$, $p < .01$) between the weak- ($\bar{x} = 2.02$, $SD = 1.18$) and the strong-disintermediation condition ($\bar{x} = 3.70$, $SD = 0.78$).

2.4.4 Measures

To measure our variables, we selected suitable and reliable scales from previously validated instruments. As suggested by Brislin (1970) and S. P. Douglas and Craig (2007), we used a bilingual committee approach in combination with pretest procedures to translate those scales into German.

The dependent variable, employee corporate entrepreneurship participation likelihood, was measured using the instrument developed by Monsen et al. (2010). Participants were asked to evaluate their likelihood of participating in a new corporate-venture team within the context of the given scenario. They provided answers on a five-point Likert-type scale (1 = *No, I would definitely not participate* to 5 = *Yes, I would definitely participate*).

The mediators employee-perceived IT support for innovation, employee-perceived work overload, and employee-perceived invasion of privacy were all assessed on a five-point Likert-type scale (1 = *does not apply at all* to 5 = *fully applies*). Again, participants had to give their evaluations in the context of the scenarios presented to them. The scales used to measure the mediator variables needed to be adapted from the original versions. The software used in the hypothetical project was referred to in place of development tools (in the case of the measure for employee-perceived IT support for innovation) and in place of information and communication technologies (in the case of the measures for employee-perceived work overload and employee-perceived invasion of privacy). Employee-perceived IT support for innovation was modeled as a reflective second-order construct being composed of the two first-order reflective constructs

employee-perceived ease of effort and employee-perceived exploration because those two are manifestations of the overall construct (Jarvis et al., 2003). To measure employee-perceived ease of effort, we used the three-item scale ($\alpha = .90$) developed by Kankanhalli et al. (2015), which we modified to refer to the collection of information and feedback. A sample item is “This software would help me save a lot of effort for collecting information and feedback.” We assessed employee-perceived exploration with a scale of three items ($\alpha = .83$) also taken from Kankanhalli et al. (2015). It was adapted to the exploration of ideas. A sample item is “This software would enable me to extensively explore new knowledge and ideas.” We used Ayyagari et al.’s (2011) three-item scale ($\alpha = .73$) to assess employee-perceived work overload. A sample item is “I would feel busy or rushed due to using this software.” Finally, to measure employee-perceived invasion of privacy, we adapted a scale of four items ($\alpha = .90$) from Ayyagari et al. (2011). A sample item is “I would feel uncomfortable that my use of this software could be easily monitored.”

We controlled for employee digital fluency because individuals with high digital fluency are able to choose and use digital technologies in accordance with their goals and understand the causes of the importance of digital technologies, therefore recognizing them as an opportunity (Briggs & Makice, 2012). Hence, it might influence the perception of resource gains and losses associated with digital affordances and employee corporate entrepreneurship participation likelihood. Employees’ digital fluency was assessed with a four-item scale ($\alpha = .83$) based on Briggs and Makice (2012). Items were rated on a five-point Likert-type scale (1 = *does not apply at all* to 5 = *fully applies*). A sample item is “I am able to achieve requested results through using digital technologies.” Additionally, we included some individual sociodemographic variables as controls. We included sex (0 = *men*, 1 = *women*) because men and women were found to differ in their rate of entrepreneurial entry (Autio et al., 2013). As younger individuals tend to be more

adventurous and therefore may have a greater willingness to participate in a new venture team (S. H. Lee & Wong, 2004), we also controlled for age (continuous variable). Furthermore, we assessed if participants had a leadership position (0 = *no*, 1 = *yes*) in their current organization. Research has shown that having a leadership position is positively related to engagement in innovative behaviors (Binnewies et al., 2007). Finally, we controlled for having a migration background (0 = *no*, 1 = *yes*) because it was found to have a significant influence on entrepreneurial intentions (Volery et al., 2013).

2.4.5 Data Analyses

We tested all hypotheses using structural equation modeling techniques with MPlus (Version 8.4). Following Preacher and Hayes (2008), we performed bootstrapping analyses to test our mediation hypotheses and indirect effects with a bootstrapping sample of 5,000. As recommended by Cohen et al. (2003) for 2x2 experimental designs, we contrast-coded the dichotomous predictor variables generativity and disintermediation. Following common practice, significance decisions for the direct effects were made based on *p*-values (Montoya & Hayes, 2017). Significance decisions concerning the mediation hypotheses were made based on bootstrap confidence intervals to account for the often-asymmetric sampling distribution of the indirect effects (Preacher & Hayes, 2008).

2.5 Results

2.5.1 Statistics and Measurement Model

Table 1 provides descriptive statistics and correlations for all variables. We ran a confirmatory factor analysis with all latent constructs (i.e., including the latent control variable employee digital fluency). Employee-perceived IT support for innovation was modeled as a

second-order construct, and all items loaded on their respective constructs. All factor loadings exceeded the minimum threshold of .40 proposed by Bagozzi and Baumgartner (1994). To validate our measurement model, we evaluated convergent validity examining the composite reliability, Cronbach's alpha, and average variance extracted of all latent constructs on the one hand and discriminant validity on the other hand. Employee-perceived work overload had the lowest Cronbach's alpha score (.73) among the tested constructs. The average variance extracted exceeded .50, satisfying the threshold suggested by Fornell and Larcker (1981). Finally, composite reliabilities were greater than .75, indicating good reliability (Bagozzi & Yi, 1988). According to Fornell and Larcker (1981), discriminant validity is demonstrated when the square root of the average variance extracted of each factor is greater than the inter-correlations between the constructs. As Table 2 shows, all conditions are met, demonstrating convergent and discriminant validity.

Table 1*Descriptive Statistics and Correlations of Study 1 Variables*

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
<i>Control</i>													
1. Age	36.91	11.06											
2. Sex	0.20	0.40	-.10										
3. Migration background	0.07	0.26	-.10	.09									
4. Leadership position	0.48	0.50	.32**	-.22**	-.05								
5. Digital fluency	4.05	0.62	-.14	-.24**	.04	.03							
<i>Independent</i>													
6. Generativity	0.02	0.50	.00	.03	.08	.04	.02						
7. Disintermediation	0.05	0.50	-.03	.19**	.18**	-.01	-.20**	.02					
<i>Mediator</i>													
8. Employee-perceived ease of effort	3.33	1.14	-.07	.18**	.14*	.04	-.10	.25**	.61**				
9. Employee-perceived exploration	3.33	0.92	.00	.07	.13	.10	-.06	.34**	.47**	.75**			
10. Employee-perceived work overload	2.70	0.80	.08	.01	-.04	-.06	-.09	-.35**	-.28**	-.34**	-.31**		
11. Employee-perceived invasion of privacy	2.52	0.96	.03	-.01	.03	.04	-.23**	.14*	-.03	.07	.08	.23**	
<i>Dependent</i>													
12. Employee corporate entrepreneurship participation likelihood	3.15	1.09	-.11	.06	.08	.08	.08	.30**	.34**	.52**	.48**	-.44**	-.11

Note. $N = 207$. Employee-perceived ease of effort and employee-perceived exploration are sub-dimensions of employee-perceived IT support for innovation. Sex is coded 0 = *men* and 1 = *women*. Leadership position is coded 0 = *no*, 1 = *yes*. Migration background is coded 0 = *no*, 1 = *yes*.

* $p < .05$, ** $p < .01$.

Table 2*Convergent and Discriminant Validity of Study 1 Variables*

Construct	α	Composite reliability	Average variance extracted	Employee-perceived IT support for innovation	Employee-perceived work overload	Employee-perceived invasion of privacy	Employee digital fluency
Employee-perceived IT support for innovation	.91	.92	.85	.92			
Employee-perceived work overload	.73	.77	.56	-.25	.75		
Employee-perceived invasion of privacy	.90	.90	.70	.07	.35	.84	
Employee digital fluency	.83	.84	.56	-.14	-.20	-.26	.75

Note. Diagonal elements in the last four columns are the square root of the average variance extracted. Non-diagonal elements in the last four columns are the latent variable correlations reported in the confirmatory factor analysis.

Confirmatory factor analysis results showed that our measurement model fitted the data well ($\chi^2 = 183.18$, $df = 111$, $p < .01$, CFI = .96, TLI = .96, RMSEA = .06, SRMR = .08; Hu & Bentler, 1999). In addition, we compared our measurement model to alternative model solutions. First, we tested Alternative Model 1, which included only the first-order factors employee-perceived ease of effort and employee-perceived exploration. Since the fit of Alternative Model 1 was not statistically significantly better ($\chi^2 = 182.94$, $df = 109$, $p < .01$, CFI = .96, TLI = .95, RMSEA = .06, SRMR = .08; $\Delta\chi^2 = 0.24$, $\Delta df = 2$, $p = .89$), we decided to keep the operationalization of employee-perceived IT support for innovation as a second-order construct. We then tested Alternative Model 2 with all measures evaluated based on the scenario loading onto one factor, which had a statistically significantly worse fit ($\chi^2 = 931.10$, $df = 118$, $p < .01$, CFI = .59, TLI = .53, RMSEA = .18, SRMR = .17; $\Delta\chi^2 = 747.92$, $\Delta df = 7$, $p < .01$).

2.5.2 Hypothesis Testing

Table 3 shows our structural model results. The mediation model (assuming full mediation) showed an acceptable model fit ($\chi^2 = 348.14$, $df = 210$, $p < .01$, CFI = .94, TLI = .92, RMSEA = .06, SRMR = .08). There was no statistically significant relationship between the control variables age, sex, leadership position, and migration background and the mediating and dependent variables. However, we found statistically significant and negative relationships between employee digital fluency and employee-perceived work overload ($\beta = -.23$, $p = .01$) as well as employee-perceived invasion of privacy ($\beta = -.30$, $p < .01$).

In line with Hypotheses 1a and 1b, we found a statistically significant and positive indirect effect of generativity ($\beta = .15$, $SE = .04$, 95% bootstrap confidence interval of the indirect effect (CI) = [0.07, 0.24]) and disintermediation ($\beta = .33$, $SE = .05$, CI = [0.23, 0.43]) on employee corporate entrepreneurship participation likelihood through employee-perceived IT

support for innovation. Both the direct effects of generativity ($\beta = .29, p < .01$) and disintermediation ($\beta = .64, p < .01$) on employee-perceived IT support for innovation and the direct effect of employee-perceived IT support for innovation on employee corporate entrepreneurship participation likelihood ($\beta = .52, p < .01$) were statistically significant and positive.

Furthermore, the indirect effects of generativity ($\beta = .06, SE = .03, CI = [0.01, 0.13]$) and disintermediation ($\beta = .05, SE = .03, CI = [0.01, 0.11]$) on employee corporate entrepreneurship participation likelihood through employee-perceived work overload were also statistically significant. Contrary to our Hypotheses 2a and 2b, the indirect effect was positive rather than negative. Both the relationships of generativity ($\beta = -.31, p < .01$) and disintermediation ($\beta = -.26, p < .01$) with employee-perceived work overload and the relationship between employee-perceived work overload and employee corporate entrepreneurship participation likelihood ($\beta = -.20, p = .01$) were statistically significant and negative.

The indirect effects of generativity ($\beta = -.01, SE = .01, CI = [-0.03, 0.01]$) and disintermediation ($\beta = .01, SE = .01, CI = [-0.01, 0.03]$) on employee corporate entrepreneurship participation likelihood through employee-perceived invasion of privacy were not statistically significant. Thus, Hypotheses 3a and 3b did not receive support. Generativity had a statistically significant and positive relationship with employee-perceived invasion of privacy ($\beta = .14, p = .05^3$), while there was no statistically significant relationship between disintermediation and employee-perceived invasion of privacy ($\beta = -.10, p = .17$). In addition, employee-perceived invasion of privacy was not significantly related to employee corporate entrepreneurship participation likelihood ($\beta = -.07, p = .30$).

³ The p -value is .05 due to rounding. It is smaller than .05.

Table 3*Structural Model Results of Study 1*

Path	β	SE	p / CI
<i>Second-order estimated paths</i>			
Employee-perceived IT support for innovation → Employee-perceived ease of effort	.96	.04	< .01
Employee-perceived IT support for innovation → Employee-perceived exploration	.89	.05	< .01
<i>Direct effects</i>			
Generativity → Employee-perceived IT support for innovation	.29	.06	< .01
Disintermediation → Employee-perceived IT support for innovation	.64	.05	< .01
Generativity → Employee-perceived work overload	-.31	.07	< .01
Disintermediation → Employee-perceived work overload	-.26	.07	< .01
Generativity → Employee-perceived invasion of privacy	.14	.07	.05
Disintermediation → Employee-perceived invasion of privacy	-.10	.07	.17
Employee-perceived IT support for innovation → Employee corporate entrepreneurship participation likelihood	.52	.07	< .01
Employee-perceived work overload → Employee corporate entrepreneurship participation likelihood	-.20	.08	.01
Employee-perceived invasion of privacy → Employee corporate entrepreneurship participation likelihood	-.07	.07	.30
<i>Indirect effects</i>			
H1a: Generativity → Employee-perceived IT support for innovation → Employee corporate entrepreneurship participation likelihood	.15	.04	[0.07, 0.24]
H1b: Disintermediation → Employee-perceived IT support for innovation → Employee corporate entrepreneurship participation likelihood	.33	.05	[0.23, 0.43]
H2a: Generativity → Employee-perceived work overload → Employee corporate entrepreneurship participation likelihood	.06	.03	[0.01, 0.13]
H2b: Disintermediation → Employee-perceived work overload → Employee corporate entrepreneurship participation likelihood	.05	.03	[0.01, 0.11]
H3a: Generativity → Employee-perceived invasion of privacy → Employee corporate entrepreneurship participation likelihood	-.01	.01	[-0.03, 0.01]
H3b: Disintermediation → Employee-perceived invasion of privacy → Employee corporate entrepreneurship participation likelihood	.01	.01	[-0.01, 0.03]

Note. $N = 207$. Employee-perceived ease of effort and employee-perceived exploration are sub-dimensions of employee-perceived IT support for innovation. The p -values of indirect effects are not reported because significance decisions are made based on confidence intervals (Preacher & Hayes, 2008).

To check for the robustness of our findings, we ran a series of alternative model tests. First, we tested a model that included direct paths from generativity and disintermediation on employee corporate entrepreneurship participation likelihood. This model did not show a statistically significantly better fit ($\chi^2 = 344.82$, $df = 208$, $p < .01$, CFI = .94, TLI = .92, RMSEA = .06, SRMR = .08; $\Delta \chi^2 = 3.32$ $\Delta df = 2$, $p = .19$). This result strengthened our confidence in the hypothesized full-mediation model because we did not find a significant direct effect of either generativity ($\beta = .11$, $p = .13$) or disintermediation ($\beta = -.02$, $p = .82$) on the dependent variable. Second, to accommodate alternative explanations for our findings, we controlled for the effect of perceived realism of the scenario presented. The results of our hypothesis testing did not change.

2.6 Discussion

2.6.1 Theoretical Implications

Our study aimed to resolve the question of how and why digital affordances relate to employee corporate entrepreneurship participation likelihood. Our results show that generativity and disintermediation trigger such tendencies via employee-perceived IT support for innovation. In line with the resource accumulation argument of conservation of resources theory (Hobfoll, 1989, 2001), employees perceive digital-affordances-related resource gains in the form of IT support for innovation (i.e., increased opportunities for idea exploration and reduced effort in idea generation and exchange). Consequently, they strive to obtain additional resources by engaging in corporate entrepreneurial behavior. Thus, our findings advance research on corporate entrepreneurship by introducing employee-perceived IT support for innovation as an important resource for, and predictor of, employee corporate entrepreneurship participation likelihood.

In contrast to our expectations, our results do not hint at digital affordances as a double-edged sword with regard to employee corporate entrepreneurship participation likelihood. Rather, our results seem to be in line with the positive view on digital affordances currently dominating the entrepreneurship literature (see Autio et al., 2018; Nambisan, 2017).

The statistically significant positive indirect effects indicate that digital affordances (i.e., generativity and disintermediation) might foster rather than reduce employee corporate entrepreneurship participation likelihood via employee-perceived work overload. In contrast to Ayyagari et al.'s (2011) results, respondents did not perceive digital affordances as causing a higher inflow of work that exceeds their processing capacities. Instead, employees seem to perceive the characteristics of generativity as decreasing work overload, which supports arguments that generative digital technologies reduce work effort (Zittrain, 2006). In addition, they seem to perceive the ability to directly and seamlessly communicate offered by digital technologies characterized by high disintermediation as helpful for dealing with work-related tasks; disintermediation facilitates cooperation (Autio et al., 2018) and finding help in case of problems or questions, which should reduce employee-perceived work overload (Tarafdar et al., 2015). In reducing work overload, digital affordances seem to be associated with perceptions of gaining resources, for example, time and support, rather than losing resources.

Employees might be willing to invest the resources saved as a result of reduced work overload (e.g., energy and support resources) to perform corporate entrepreneurial behavior. This hints at additional support for the resource accumulation argument of conservation of resources theory (Hobfoll, 1989, 2001). However, as expected, we found a negative relationship between employee-perceived work overload and employee corporate entrepreneurship participation likelihood. This is consistent with the studies conducted by Ng and Feldman (2012) and de Clercq et al. (2016). It is also in line with the resource conservation argument of conservation of

resources theory (Hobfoll, 1989, 2001), stating that individuals experiencing resource losses conserve their remaining resources and engage less in behaviors that consume additional resources.

Our results did not show that employee-perceived invasion of privacy mediated the relationship between digital affordances and employee corporate entrepreneurship participation likelihood. We only found that high generativity fosters employee fears that their privacy could be invaded. This indicates that generativity is associated with a loss of resources, such as a reduction of autonomy, control, or private time (Halbesleben et al., 2014). Contrary to our expectations, disintermediation was not significantly related to employee-perceived invasion of privacy. The increased information inflow resulting from the ability to communicate directly does not seem to make employees feel that their privacy has been compromised by work and work-related digital technologies. According to Ayyagari et al. (2011), the perception of an invasion of privacy is caused, in particular, by those digital technologies that make employees accessible to others and, therefore, constantly reachable. Disintermediation alone brings along increased communication inflow. But, unlike generativity, it does not provide access to those messages at any time and from any place and hence does not necessarily enable constant connectivity. Consequently, the feeling of an invasion of privacy might not arise. Thus, while generativity seems to be associated with resource loss in the form of losses of autonomy and control, disintermediation does not.

Examining the relationship between employee-perceived invasion of privacy and employee corporate entrepreneurship participation likelihood, we found this relationship to be not statistically significant. Employees facing the loss of constructive resources such as autonomy and control as a result of digital technologies with high generativity do not seem less willing to perform corporate entrepreneurial activities as predicted by the resource conservation argument

(Hobfoll, 1989, 2001). An explanation for this could be that employees accept and maybe even expect an invasion of privacy as a side effect of advances in digital technologies (Ayyagari et al., 2011). Moreover, Allen et al. (2007) found that employees deem electronic surveillance at the workplace as necessary and even beneficial: it protects organizations from employee dishonesty and noncompliance and increases employee security and productivity by promoting efficiency.

While, in general, the positive notion of digital affordances seems to dominate, our results at least provide some support that this does not come without a cost. While generativity fosters employee-perceived IT support for innovation that enhances employee corporate entrepreneurship participation likelihood, employees still seem to feel an invasion of privacy. This sense might cause other negative consequences than those we focused on in our study. A future investigation of these potentially countervailing processes (resource gains versus resource losses) stemming from generativity seems warranted.

Conservation of resources theory (Hobfoll, 1989, 2001) has mainly been applied to predict stress outcomes. Only recent studies considered conservation of resources theory to examine the implications of resource gains and losses for motivational outcomes (Hobfoll et al., 2018). It has not yet been used to predict employee corporate entrepreneurship participation likelihood. By doing so, we were able to contribute to the literatures on the conservation of resources theory and on corporate entrepreneurship. We also add to recent research by Gawke et al. (2017, 2018), who took a demands-resources perspective on the consequences of employee corporate entrepreneurship. We do this by introducing a resource perspective into the examination of the determinants of employee corporate entrepreneurship. Our results suggest that organizations can foster employee corporate entrepreneurship participation by providing digital technologies with high capacities for generativity and disintermediation. This would lead to resource gains in the form of support (e.g., IT support for innovation) and energy resources (e.g., time) that can be

invested to gain additional resources by engaging in corporate entrepreneurial activities and that reduce the investments required to perform such activities. By taking a conservation of resources perspective, we contribute to the corporate entrepreneurship literature with insights into how to foster the likelihood of employee engagement in corporate entrepreneurial activities (Kuratko, Hornsby, & Hayton, 2015).

In addition, by conducting one of the first empirical studies investigating digital affordances, we answered the call of Majchrzak and Markus (2013) to empirically examine affordances. We were able to provide insights into the mechanisms triggered by digital affordances regarding employee corporate entrepreneurship participation likelihood. Our results indicate that digital affordances not only enable external entrepreneurial phenomena like the emergence of new start-ups and entire entrepreneurial ecosystems (Autio et al., 2018) but can also foster corporate entrepreneurial activities. They enable these via employee-perceived IT support for innovation and via the reduction of employee-perceived work overload. Thus, we were able to transfer the digital affordances concept into the realm of corporate entrepreneurship, thereby contributing to research on both digital affordances and corporate entrepreneurship. This answers Autio et al.'s (2018) call to closer examine the role of digital technologies and related affordances in entrepreneurial processes. Our study adds to emerging literature streams on digital entrepreneurship and digital innovation and addresses Nambisan et al.'s (2017) call to further investigate how digital technologies enable and constrain innovation as well as participation in innovation. Digital technologies enable innovative activities by affording generativity and disintermediation, which are perceived as supportive of innovative behaviors such as corporate entrepreneurship.

2.6.2 Managerial Implications

Our findings may help managers and consultants better understand the mediating mechanisms in the relationship between digital affordances and employee corporate entrepreneurship participation likelihood. Perceiving that innovative activities are supported and that work overload can be reduced by the organization's digital technologies might be relevant mechanisms for fostering employee participation in corporate entrepreneurship. This could be achieved by providing a digital infrastructure that is characterized by high generativity and high disintermediation.

To attain high generativity (Zittrain, 2006, 2007, 2008), organizations might install digital technologies that are cloud-based and can be accessed from a multitude of devices ranging from desktop computers up to employees' smartphones using apps (accessibility). Additionally, those digital technologies should be easily extensible (leverage) so that more functions might be added with minimal effort. This could be achieved by implementing application-programming interfaces that allow digital technologies to be easily combined and integrated. Those application programming interfaces also enable the modification of digital technologies (adaptability). Furthermore, their use should be easy and intuitive to secure ease of mastery.

To ensure high disintermediation, digital technologies should allow direct and seamless exchange among employees (Autio et al., 2018). This will support innovative behaviors by facilitating the collection of information and feedback and by helping them to explore and experiment with new ideas. Thus, organizations might install internal social networks or provide chat programs and feedback tools (Chow & Ng, 2016; Fieseler & Fleck, 2013). Moreover, highly integrated databases might help employees to get the necessary information.

However, we found that generative digital technology might lead to an increased concern that employee privacy could be invaded. Therefore, we recommend organizations that want to invest in a modern digital infrastructure to create transparency about which data will be tracked and what happens with that data. It should also be made clear that the organization has no intention of accessing employees' private data and that only data that is relevant for assessing employee job performance will be saved (Alge, 2001). Additionally, monitoring practices should be used selectively with respect to the employees' roles and authority (e.g., applying these only to employees who have access to important information assets) rather than to all employees (C. Lee et al., 2016).

2.6.3 Limitations and Implications for Future Research

Our study is a first step to understanding how and why digital affordances influence employee corporate entrepreneurship participation likelihood. As all empirical studies tapping into uncharted territory, our study has some limitations that offer a rich ground for future research. First, on average, our respondents were highly digitally fluent. Digital fluency allows employees to choose and use digital technologies according to their goals and to understand their importance (Briggs & Makice, 2012). Consequently, digitally fluent employees are better able to recognize the support and the opportunities provided by digital affordances and should be less vulnerable to their negative consequences (S. Chen et al., 2009). Thus, future research should validate our findings with respondents covering a broader range of digital fluency.

Second, the specific nature of our sample might have influenced our results. Our respondents were employees in Germany, but employee protection, worktime regulations, and attitudes toward overtime differ between countries (Wharton & Blair-Loy, 2002). Consequently, the relationships between digital affordances and employee perceptions regarding work overload

and invasion of privacy may differ, and future studies may compare different country samples. Previous research (e.g., Hornsby et al., 2009; Jessri et al., 2020; Monsen et al., 2010) provides support for the suitability of our sample, and we eliminated respondents who judged our scenario to be unrealistic for them. Nevertheless, it might be possible that some lower-level employees (even though having managerial tasks) may not have full freedom to decide on whether to join corporate entrepreneurial projects. They might, however, be able to perform entrepreneurial behaviors within projects to which they are assigned (Baum & Rabl, 2019). Thus, future studies might examine the role of digital affordances regarding the entrepreneurial behavior of employees within already assigned projects.

Third, digital affordances refer to action potentials that digital technologies represent for users with certain characteristics and purposes. It is thus important to consider the interactions between individuals and organizations and the digital technologies they use (Majchrzak & Markus, 2013). Accordingly, future research could examine which personality traits and organizational characteristics influence the perception of digital affordances and how the mediating mechanisms theorized in this study are affected by them. In this context, future research might investigate the conditions under which the double-edged sword we theorized about becomes relevant.

Finally, when applying conservation of resources theory (Hobfoll, 1998, 2001) to explain employee corporate entrepreneurship participation likelihood, on the one hand, taking a crossover perspective (Hobfoll et al., 2018) might be another promising avenue for future research. For example, it would be interesting to examine the impact of coworkers perceiving resource gains induced by digital technologies on employee perceptions and their corporate entrepreneurship participation. On the other hand, future research may also delve into exploring gain and loss spirals (Hobfoll, 2001; see, e.g., Hakanen et al., 2008) that might be associated with corporate

entrepreneurial activities and examine reversed causal effects. In our experimental study with digital affordances as manipulated independent variables and employee corporate entrepreneurship participation likelihood as the dependent variable, reversed causality is no issue. Examining how the resource gains and losses associated with corporate entrepreneurial activities may, in turn, influence employee perceptions of digital affordances might be an interesting question for future studies.

2.7 Conclusion

Our study constitutes an initial step to enhancing our understanding of the processes that emanate from digital affordances. It helps resolve the question of how and why digital affordances influence employee corporate entrepreneurship participation likelihood. Building and empirically testing a model based on conservation of resources theory, we showed that digital affordances do not seem to be a double-edged sword per se. Generativity and disintermediation have a positive indirect influence on employee corporate entrepreneurship participation likelihood. The main mechanisms behind these positive effects are enhanced employee-perceived IT support for innovation and reduced employee-perceived work overload. At least in our managerial sample, the “light side” of digital affordances seems to dominate in relation to corporate entrepreneurial behavior.

3. Can Digital Technology Support Stimulate Employee Intrapreneurial Behavior? The Moderating Role of Organizational and Personal Resources

3.1 Abstract

Drawing on the model of the corporate entrepreneurship process and the conservation of resources theory, this chapter examines the relationship between digital technology support and employee intrapreneurial behavior. We propose management support for innovation as an organizational resource and intrapreneurial self-efficacy as a personal resource that moderate this relationship. Findings from a metric conjoint experiment with 1,360 decisions nested within 85 employees showed that support by collaborative technologies, support by social media, and support by intelligent decision support systems were significant predictors of employee intrapreneurial behavior. However, the relative impact of support by these digital technologies varied with different levels of management support for innovation and intrapreneurial self-efficacy.

Keywords: conjoint experiment; conservation of resources theory; digital technology support; intrapreneurial self-efficacy; intrapreneurship; management support for innovation.

3.2 Introduction

Increasingly, organizations address growing environmental turbulence and competition by fostering intrapreneurship (Ireland et al., 2003). They do this to secure their competitive advantage in the global marketplace (Blanka, 2019). However, to successfully establish intrapreneurial projects, organizations need to know how to encourage individual intrapreneurial behavior (Hornsby et al., 2002). Employee intrapreneurial behavior is defined as “an individual employee’s agentic and anticipatory behaviors aimed at creating new businesses for the organization (i.e., venture behavior) and enhancing an organization’s ability to react to internal and external advancements (i.e., strategic renewal behavior)” (Gawke et al., 2017, p. 89). Despite the importance of knowing about the determinants of employee intrapreneurial behavior, research in this area is still scarce and fragmented (Blanka, 2019).

Digital technologies enhance organizations’ access to resources and enable a more effective exchange, combination, and integration of those resources (Amit & Han, 2017). According to the information systems and digital entrepreneurship literatures (see, e.g., Junglas et al., 2019; Nambisan, 2017; Nambisan et al., 2017; Steininger, 2019; von Briel et al., 2018), digital technologies are facilitators and drivers of innovative and entrepreneurial activities. They are “products or services that are either embodied in information and communication technologies or enabled by them” (Lyytinen et al., 2016, p. 49). So far, scholars have largely focused on examining the effect of digitalization on entrepreneurial activities (e.g., Haarhaus et al., 2018), but have mostly neglected that digital technologies may also enable intrapreneurial activities by making it easier for actors in existing organizations to invent new methods to create, deliver, and capture value (Autio et al., 2018; Steininger, 2019).

In this chapter, we address whether and under what conditions the support by different types of digital technologies (i.e., collaborative technologies, social media, and intelligent decision support systems) contributes to employee intrapreneurial behavior. *Collaborative technologies* are tools that allow for synchronous interactions (S.-H. Lee et al., 2006). *Social media* are “a group of internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user generated content” (Kaplan & Haenlein, 2010, p. 61). *Intelligent decision support systems* are “interactive computer-based systems that use data, expert knowledge, and models for aiding organizational decision-makers in semi-structured problems incorporating problem-solving techniques of artificial intelligences” (Sarma, 1994, p. 403).

Hornsby et al.’s (1993) model of the intrapreneurial process in organizations suggests that the decision to act intrapreneurially results from an interaction between a precipitating event, organizational characteristics, and individual characteristics. Support by digital technologies can function as such a precipitating event; such support provides the impetus to engage in intrapreneurial behavior because it creates new opportunities for intrapreneurship (Junglas et al., 2019). In this study, we propose an interaction of digital technology support with management support for innovation, which is an organizational characteristic that plays an important role in the intrapreneurial process (Hornsby et al., 2009), and employee personal characteristics, which determine how employees react to digital technologies (Hornsby et al., 1993). *Intrapreneurial self-efficacy*, an employee’s belief in her or his capabilities to perform tasks associated with innovation initiatives, might be an important individual characteristic influencing an employee’s ability to recognize the enabling function of digital technologies (Globocnik & Salomo, 2015). By considering both organizational and individual characteristics as contingencies, our study offers valuable clues as to the circumstances under which digital technology support enables

employee intrapreneurial behavior. With this, we add to von Briel et al.'s (2018) theorizing about digital technologies as enablers of entrepreneurial processes.

We draw on the conservation of resources theory that has been successfully used to predict various stress and motivational outcomes in organizational settings (Hobfoll, 2001; Hobfoll et al., 2018). Digital technologies have been theorized to reduce the resource investments necessary to engage in entrepreneurial (von Briel et al., 2018) and, therefore, also intrapreneurial activities, making it easier to do so. Conservation of resources theory posits that the resources to which individuals have access influence their behavioral decision-making (Hobfoll, 2001). By applying conservation of resources theory to questions of intrapreneurship, our study provides further insights into the interaction of personal and organizational resources and the role of this interaction in the intrapreneurial process.

We also contribute to the intrapreneurship literature by enhancing knowledge on encouraging employee willingness to perform intrapreneurial behaviors, which is a key factor for organizations' entrepreneurial strategies (Hornsby et al., 2002). In addition, our study increases our understanding of how the internal organizational environment affects employee intrapreneurial behavior, which is still far from complete (Rigtering et al., 2019).

Although there is a growing body of research theorizing how digital technologies might enable innovative and entrepreneurial activities (e.g., Nambisan et al., 2017, 2018; von Briel et al., 2018), empirical research in this domain remains scarce. Despite the importance of examining the determinants of an individual employee's innovative and entrepreneurial activities (Hornsby et al., 2002; Kuratko et al., 2005), these studies do not, for the most part, focus on the individual. Our study addresses this void and contributes to the intersection of the information systems and entrepreneurship literatures. With this, we also contribute to answering Nambisan's (2017) call to more closely examine digital technologies' role in entrepreneurial processes.

3.3 Theory and Hypotheses

3.3.1 A Resource Perspective on the Relationship Between Digital Technology Support and Employee Intrapreneurial Behavior

Conservation of resources theory defines resources as “those objects, personal characteristics, conditions, or energies that are valued by the individual or that serve as a means for attaining these objects, personal characteristics, conditions, or energies” (Hobfoll, 1989, p. 516). According to conservation of resources theory, individuals strive to obtain new resources and avoid resource losses (Hobfoll, 1989, 2001). The resource accumulation argument of the conservation of resources theory (Hobfoll, 1989, 2001; Ng & Feldman, 2012) postulates that individuals strive to obtain new resources. When people acquire new resources, they are shielded from resource loss. At the same time, individuals become capable of further resource gains because they have more resources that can be invested to acquire additional resources (Halbesleben et al., 2014; Hobfoll, 2001). The resource conservation argument, in contrast, posits that individuals experiencing resource loss engage less in behaviors that consume additional resources. Thus, employees may adopt a defensive posture to conserve their remaining resources (Halbesleben et al., 2014; Hobfoll, 2001; Hobfoll et al., 2018).

Hence, according to conservation of resources theory (Hobfoll, 1989, 2001), individuals are likely to engage in intrapreneurial behavior when they expect the resource gains associated with their behavior to outweigh the associated resource investments. On the one hand, employee intrapreneurial behavior can lead to resource gains in the form of increased personal resources (e.g., self-efficacy, Bandura, 1997; optimism, Carver & Scheier, 2002; or resilience, Masten, 2001) by allowing employees to experience success, to achieve action goals, and to master challenges (Gawke et al., 2017). Additionally, it might also result in financial resource gains

(e.g., via profit sharing; Monsen et al., 2010). On the other hand, engagement in intrapreneurial behavior also implies considerable resource investments, such as additional energy and time (Scott & Bruce, 1994) and personal resources to deal with risk and uncertainty (McGrath, 1999; McGrath & MacMillan, 2000). However, support by digital technologies decreases the resource investment necessary to perform intrapreneurial activities (von Briel et al., 2018), leading to a net resource gain. Therefore, digital technology support provides an opportunity for employees to gain additional resources at lower costs.

Collaborative technologies offer an opportunity for a facilitated interaction with business agents inside and outside the organization (Meroño-Cerdán et al., 2008) and therefore help employees to better coordinate their work with others (Doll & Deng, 2001). They can be used to distribute and share individual experiences (Bhatt et al., 2005) and allow the efficient storage and retrieval of codified knowledge (Adamides & Karacapilidis, 2006). Hence, they are a tool for information dissemination and data access across functional boundaries and hierarchical levels. Collaborative technologies lower the effort and thus the resource investments associated with corporate information searches (Meroño-Cerdán et al., 2008). In doing so, they facilitate sharing knowledge and information and the exchange of ideas (Bélanger & Allport, 2008; Doll & Deng, 2001). Therefore, they reduce the amount of energy and time that needs to be invested in performing intrapreneurial behaviors (Schneckenberg et al., 2015). Moreover, collaborative technologies allow working with no distance limitations (Meroño-Cerdán et al., 2008). As such, they allow employees from locally dispersed plants to get together to innovate, thereby reducing the resources required for coordination (Bafoutsou & Mentzas, 2002).

According to Leonardi et al. (2013), social media technologies allow employees to send messages to everyone in the organization or specific coworkers and reveal particular colleagues as communication partners. They offer employees the opportunity to post, edit, and sort text or

files linked to themselves or others, and enable the viewing of messages, connections, text, and files communicated, posted, edited, and sorted by other organizational members at any time. Therefore, social media make communication visible, which leads to an enhanced awareness of who knows what and whom in organizations. This, in turn, allows employees to better recombine existing ideas into new ones and avoid duplicating work (Leonardi, 2014), saving time and energy resources in the intrapreneurship process. Moreover, social media facilitate social and interpersonal relationships by enabling a faster information flow and increasing knowledge sharing (Havakhor et al., 2018; Qualman, 2010; Stock & Groß, 2016; Treem & Leonardi, 2012). This, in turn, is a driver of innovation outcomes such as intrapreneurship (Leonardi, 2014).

Additionally, the easier interaction among employees from different geographic areas and cultures may generate creative ideas, facilitating intrapreneurial behavior (Lam et al., 2016). Furthermore, social media enable the externalizing, disseminating, and discussion of information and ideas and the combination and sharing of knowledge. Thus, they can enrich and expand individual's cognitive abilities to perform complex innovation tasks and facilitate the generation and co-creation of new ideas (Sigala & Chalkiti, 2015). This should make it easier to engage in intrapreneurial behavior and reduce the resource investments required to do so.

Intrapreneurial activities are characterized by uncertainty (McGrath, 1999; McGrath & MacMillan, 2000), making the risk of failure inherently high (Shepherd et al., 2013). Intelligent decision support systems can reduce this risk, decreasing the resources necessary to deal with it. Those systems help screen, shift, and filter the increasing overflow of data, information, and knowledge in times of accelerating digitalization, enabling effective and productive decision-making (Jantan et al., 2010). Moreover, intelligent decision support systems extend cognition in the face of complexity (Jarrahi, 2018). This should decrease the cognitive resources that individuals have to invest. Additionally, intelligent decision support systems facilitate decision-

making processes with uncertainty or incomplete information (Jantan et al., 2010), as is typical for intrapreneurial activities (Shepherd et al., 2013). They provide real-time insights about early-warning signs and help detect anomalies and ensure timely corrective actions (Jarrahi, 2018). Therefore, intelligent decision support systems might decrease the likelihood of failure of the intrapreneurial activity (Shepherd & Patzelt, 2017). They reduce the risk and, therefore, the personal resources that need to be invested. Hence, according to conservation of resources theory, support by digital technologies should foster employee intrapreneurship activities. Thus, we propose:

Hypothesis 1: Support by a) collaborative technologies, b) social media, and c) intelligent decision support systems are positively related to employee intrapreneurial behavior.

3.3.2 The Moderating Role of Management Support for Innovation

Following conservation of resources theory, an individual's resource pool influences whether situations are defined as threats or opportunities (Ito & Brotheridge, 2003). Those with more resources at their disposal are better positioned to invest resources and shielded against resource loss (Hobfoll, 2001). Employees with stronger resource pools are more likely to define a situation as an opportunity. In general, individuals strive to gain more resources (Hobfoll, 1989). A larger resource pool should also increase the likelihood that individuals will seek opportunities to invest resources to achieve resource gains (Hobfoll & Shirom, 2001). Hence, employees with more resources are more sensitive to opportunities (Cropanzano & Wright, 2001). Such employees should be more likely to recognize the opportunity presented by the support of digital technologies to gain additional resources through intrapreneurial activities at a lower cost.

Management support for innovation is an important resource in the job context that should increase employee sensitivity to opportunities (Halbesleben et al., 2014). It is defined as

“the willingness of top-level managers to facilitate and promote entrepreneurial behavior, including the championing of innovative ideas and providing the resources people require to take entrepreneurial actions” (Kuratko et al., 2005, p. 703). Management support for innovation is characterized by a quick adoption of employee ideas, the recognition of people who bring ideas forward, support for small experimental projects, and seed money to get projects off the ground (Hornsby et al., 1993). According to Gumusluoğlu and Ilsev (2009), employees with management support for innovation should feel encouraged to take more risks. When top management promotes the generation of new ideas, employees should be searching more actively for new opportunities (Alpkan et al., 2010). Hence, they should be more likely to recognize the opportunities provided by digital technology support.

Additionally, management support for innovation encourages outside of the box thinking and acting (Acharya & Taylor, 2012). This, in turn, makes it more likely that the opportunities provided by digital technology support will be recognized (Ozgen & Baron, 2007). Management support for innovation creates the perception that exploratory behavior, creative problem solving, and proactive opportunity-seeking are valued (de Villiers-Scheepers, 2012). The more employees perceive that management supports the seeking and recognition of new business opportunities, the more they should feel inclined to seek out those opportunities (Dimov, 2007; Zampetakis et al., 2009). Hence, they should be better positioned to recognize digital technology support as offering an opportunity to gain additional resources through intrapreneurial activities at a lower cost. Thus, in line with conservation of resources theory, we propose:

Hypothesis 2: Management support for innovation moderates the relationships of support by a) collaborative technologies, b) social media, and c) intelligent decision support systems with employee intrapreneurial behavior such that the positive relationships are stronger (weaker) when management support for innovation is high (low).

3.3.3 The Moderating Role of Intrapreneurial Self-Efficacy

As stated above, a larger resource pool should make it more likely that individuals seek opportunities to invest resources to achieve resource gains (Hobfoll & Shirom, 2001). Following Globocnik and Salomo (2015), employees' intrapreneurial self-efficacy might also play an important role when innovating with digital technologies. Intrapreneurial self-efficacy can be characterized as a personal resource (Hobfoll, 2001). "Efficacy beliefs influence how people feel, think, motivate themselves, and behave" (Bandura, 1993, p. 118). Employees with high intrapreneurial self-efficacy levels accept higher risk levels and have higher intrinsic motivation for intrapreneurial tasks (Globocnik & Salomo, 2015). They tend to see more opportunities because they have strong confidence in their abilities and focus on finding those opportunities (Krueger & Dickson, 1993). Those who are confident that they can act intrapreneurially (i.e., have a high intrapreneurial self-efficacy) are more likely to recognize opportunities and persist with the endeavor (Sardeshmukh & Corbett, 2011). This accords with the results of Krueger and Dickson (1994), who found a positive relationship between self-efficacy beliefs and the perception of opportunities. Consequently, employees having intrapreneurial self-efficacy resources at their disposal should be more likely to recognize the opportunity offered by digital technologies to gain additional resources through intrapreneurial activities at a lower cost. Thus, we propose:

Hypothesis 3: Intrapreneurial self-efficacy moderates the relationships of support by a) collaborative technologies, b) social media, and c) intelligent decision support systems with employee intrapreneurial behavior such that the positive relationships are stronger (weaker) when intrapreneurial self-efficacy is high (low).

3.3.4 The Interplay of Digital Technology Support, Management Support for Innovation, and Intrapreneurial Self-Efficacy

According to Halbesleben et al. (2014), the value of resources and their influence depends on the individual context and hence, on employees' personal characteristics. Therefore, the hypothesized positive effect of management support for innovation might differ for employees differing in their characteristics and resources. This accords with Hornsby et al. (1993), who theorize the decision to act intrapreneurially as resulting from an interaction between a precipitating event such as receiving the support of digital technologies and organizational and individual characteristics.

Lacking confidence in their intrapreneurial capabilities (i.e., low intrapreneurial self-efficacy) will make employees feel frustrated. Consequently, they will reduce their innovative undertakings (Alpkan et al., 2010; Gupta et al., 2004). Therefore, employees with lower levels of intrapreneurial self-efficacy might be in particular need of management support for innovation and are expected to highly value those support resources. When finding new ideas is encouraged and rewarded by the management, these employees should be more motivated to find new opportunities. Furthermore, employees with a high intrapreneurial self-efficacy believe in their ability to successfully act in an intrapreneurial manner (e.g., recognizing opportunities and elaborating ideas) even without support resources (Globocnik & Salomo 2015).

Conversely, employees with a low intrapreneurial self-efficacy might be especially in need of support resources in the form of management support for innovation. Hence, employees with low levels of intrapreneurial self-efficacy should particularly benefit from receiving management support for innovation; they are primed to better recognize the opportunity provided by digital technologies. Thus, we propose:

Hypothesis 4: Management support for innovation has a stronger positive moderating effect on the relationship between support by a) collaborative technologies, b) social media, and c) intelligent decision support systems on the one hand and employee intrapreneurial behavior on the other hand when intrapreneurial self-efficacy is low rather than high (three-way interaction).

3.4 Method

3.4.1 Sample

We used a metric conjoint experimental design to examine our research questions. The situation presented to participants should be familiar to them to ensure that results are not biased by artificial responses (Aguinis & Bradley, 2014; Aiman-Smith et al., 2002; Cavanaugh & Fritzsche, 1985). Therefore, we were only recruiting employees who have a realistic chance of being able to perform intrapreneurial behaviors. Participants were recruited via the professional network service Xing, Germany's biggest business network (Hofeditz et al., 2017). We contacted Xing users who matched our inclusion criteria, those who worked full-time in for-profit organizations in Germany's manufacturing sector. Our study focused on the manufacturing sector because it is the sector in Germany with the highest innovation expenditures (German Federal Ministry of Education and Research, 2019) and thus particularly interesting for examining intrapreneurial behavior. Potential study participants who accepted our contact request received an additional message including further information and a link to the study questionnaire.

We sent the link to the questionnaire to 363 employees. Of those, 106 provided complete answers, which reflects a response rate of 29.20%. Additionally, we checked our inclusion criteria via corresponding questions included in the survey. In total, 95 participants provided

complete answers and matched the inclusion criteria. After checking for test-retest reliability, we had to exclude 10 participants due to reliability issues leading to a final sample size of 85.

In our final sample, 20.00% of participants were female, which approximately matches the proportion of women working full-time in the German manufacturing sector (German Federal Statistical Office, 2020). The average participant was 42.95 years old and had 19.25 years of working experience. Among participants, 81.18% had a leadership position in their respective organizations. Regarding hierarchy level, 8.24% held operational positions, 31.76% had lower-management positions, 36.47% middle-management positions, and 23.53% upper-management positions.⁴ This is in accordance with Hornsby et al. (2009), who stated that actors at different hierarchical levels – ranging from operational level employees to upper managers – are involved in intrapreneurial activities. Thus, our sample includes realistic targets for corporate entrepreneurial engagement (Baum & Rabl, 2019; Monsen et al., 2010).

3.4.2 Design of the Conjoint Experiment

In metric conjoint experiments, participants evaluate several hypothetical scenarios (i.e., profiles) that are described by a combination of decision attributes (Brundin et al., 2008). After each scenario, participants had to make decisions (e.g., decision to join an intrapreneurial project). Decomposing participant evaluations into the underlying structures (Louviere, 1988), conjoint experiments allow us to examine the specific determinants of employee intrapreneurial behavior. Conjoint experiments are widely used in (corporate) entrepreneurship research (see, e.g., Baum & Rabl, 2019; Behrens & Patzelt, 2016; Monsen et al., 2010). Making assessments based on only a few limited cues is consistent with observations that real-life decision-makers typically refer to between three and seven attributes when deciding (Brundin et al., 2008; Stewart,

⁴ Holding a management position does not necessarily go along with having a leadership function (Yukl, 2013).

1988). Moreover, evidence suggests that the decision policies actually used by decision-makers are significantly reflected by conjoint experiments, even in artificial situations (Brundin et al., 2008; K. R. Hammond & Adelman, 1976). Furthermore, by enabling the collection of real-time data on individuals' decisions, the results obtained from a conjoint analysis are less prone to introspective and self-report biases commonly found in interview and survey data (Fischhoff, 1988; Monsen et al., 2010; Shepherd & Zacharakis, 1997). Drawing on an experimental design also secures a high level of internal validity (Aguinis & Bradley, 2014). The conjoint approach is thus particularly suited for our research purpose.

The decision situations in our conjoint experiment were described using four manipulated variables (the three independent variables support by collaborative technologies, support by social media, and support by intelligent decision support systems and the moderator variable management support for innovation) varying across two levels (“present” or “not present” for the three independent variables and “high” or “low” for management support for innovation) yielding 16 possible combinations of attribute levels. Using a design with full replication would have yielded 32 profiles and thus entailed a risk of unreliable answers, participant fatigue, and dropouts. Therefore, we refrained from a full replication of profiles and decided to replicate four profiles to check for test-retest reliability. This is consistent with the suggestions of Aiman-Smith et al. (2002) and several studies using conjoint experiments (see, e.g., Drover et al., 2014; Holland & Garrett, 2015; Murnieks et al., 2016). In addition to these 20 profiles, a “warm-up” profile and a bogus scenario were added. These latter two were excluded from the statistical analysis. Furthermore, we randomized profile presentation and used two versions of the experiment differing in the order of the decision criteria to reduce the probability of order effects (Brundin et al., 2008).

The online survey started with a scenario description asking respondents to imagine that they had identified a new and interesting business opportunity while chatting with colleagues. Following Monsen et al. (2010), the innovative character of the business opportunity, the need to promptly form a project team to realize it, and the potential negative career consequences were emphasized. These elements reflect the innovative, proactive, and risky characteristics of intrapreneurial behavior (Miller, 1983). We accounted for the structural dimensions of a new corporate venture (Sharma & Chrisman, 1999) by stating that, if successful, the project might result in a new strategic business unit or an independent spin-off. Moreover, participants were told to consider the project under the current economic conditions in Germany. They were also asked to make several assumptions: that all other parameters of the project and the environment were equal for all scenarios, that all project participants worked under the same four conditions (e.g., the manipulated variables), and that except for those, the type and scope of the hypothetical project would be comparable to current or previous projects in their organization. The scenario introduction was followed by presenting the decision profiles (each including the dependent variables). After that, respondents were asked to answer a post-experiment questionnaire that includes measures of the individual moderator variables and the control variables.

3.4.3 Measurement

To measure our variables, we selected suitable and reliable measures from previously validated instruments. Scales for which no validated German scales existed were translated using a bilingual expert approach (Brislin, 1970; S. P. Douglas & Craig, 2007).

3.4.3.1 Dependent Variables

Employee intrapreneurial behavior was captured by two variables after each decision profile: employee corporate entrepreneurship participation likelihood and employee likelihood of intrapreneurial behavior. Employee corporate entrepreneurship participation likelihood was measured using an item developed by Monsen et al. (2010). Participants were asked (framed by the decision attributes) to evaluate their likelihood of participating in a corporate new-venture team. They provided responses on a seven-point Likert-type scale (1 = *no, definitely not* to 7 = *yes, definitely*). To better reflect the agentic and proactive nature of employee intrapreneurial behavior, we also assessed employee likelihood of intrapreneurial behavior with a self-developed item based on Monsen et al. (2010). This reads, “Based on the description of the corporate entrepreneurial project above, how do you rate the likelihood that you would initiate and advance such a project in your firm on your own accord?” It was measured using the same seven-point Likert-type scale described above.

3.4.3.2 Variables Manipulated in the Conjoint Experiment

The variables support by collaborative technologies, support by social media, support by intelligent decision support systems, and management support for innovation were manipulated in our conjoint experiment. In the digital technology support manipulations, participants were provided with examples of the respective digital technology to increase comprehensibility (see examples in parentheses). Support by collaborative technologies (e.g., instant messaging services, project management systems, work and task management systems) captured whether employees could draw on collaborative technologies for collaborating in the project (in the “present” condition) or not (in the “not present” condition). Support by social media (e.g., social networks, blogs, content communities) captured whether employees have the possibility (in the “present”

condition) or do not have the possibility (in the “not present” condition) to use social media within the project. Support by intelligent decision support systems (e.g., intelligent predictive systems, text mining, machine learning) captured whether employees could consult intelligent decision support systems for the project work (in the “present” condition) or not (in the “not present” condition). The full specifications are shown in the Appendix.

To ensure the practical relevance and external validity of our manipulations of digital technology support, we conducted a supplementary study with 109 respondents who fulfilled the same inclusion criteria as in our main study. We asked participants to rate how frequently collaborative technologies, social media, and intelligent decision support systems are used in their organizations on a five-point Likert-type scale (1 = *never* to 5 = *always*). A total of 31.19%, 25.69%, and 43.12% of the participants, respectively, stated that collaborative technologies are never or rarely, occasionally, or often or always used in their organizations ($\bar{x} = 3.17$, $SD = 1.28$). Regarding social media, 60.55%, 28.44%, and 11.01% of the participants indicated that these technologies are never or rarely, occasionally, or often or always used in their organizations ($\bar{x} = 2.28$, $SD = 1.05$). For intelligent decision support systems, 88.99%, 8.26%, and 2.75% of the participants, respectively, specified that these are never or rarely, occasionally, or often or always used in their organizations ($\bar{x} = 1.43$, $SD = 0.76$). Thus, although intelligent decision support systems do not seem to be widely-used yet, results from our supplementary study show that the full range of support by collaborative technologies, social media, and intelligent decision support systems is present in organizations. The results underline that it is legitimate to assume that there are situations in which employees do not have the support of these digital technologies. This indicates that our experimental conditions are practically relevant and externally valid.

The manipulation of management support for innovation was based on the definition by Kuratko et al. (2005). In the “high” condition, management to a large degree facilitates and

promotes innovative behavior by strongly championing innovative ideas and providing the resources people require to take innovative actions. In the “low” condition, management facilitates and promotes employee innovative behavior to a minor degree by weakly championing innovative ideas and hardly providing the resources people require to take innovative actions.

3.4.3.3 Variables From the Post-Experiment Survey

The moderator intrapreneurial self-efficacy was measured with a 10-item scale ($\alpha = .86$) from Globocnik and Salomo (2015). A sample item is “I have confidence in generating new ideas.” The items had to be rated on a five-point Likert-type scale (1 = *does not apply at all*, to 5 = *fully applies*). Additionally, we controlled for prior entrepreneurial experience, personal initiative, and willingness to take risks. These variables reside on the individual level and are treated accordingly in our analysis. We controlled for employees’ willingness to take risks because it has been found to negatively influence individual intrapreneurial intentions (E. J. Douglas & Fitzsimmons, 2013). We assessed this using a single item from Beierlein et al. (2014). As prior entrepreneurial experience was found to be the most important human capital variable determining entrepreneurial intentions (Fitzsimmons & Douglas, 2011), we included it as a control variable, measured via the sum score out of four binary items (0 = *no*, 1 = *yes*) developed by Peterman and Kennedy (2003). A sample item is “Have you ever started a business?” *Personal initiative* was also added as a control variable. This is an individual’s tendency to engage in work behaviors characterized by a self-starting nature, a proactive approach, and being persistent in overcoming difficulties that arise in pursuing a goal (Frese et al., 1996; Frese et al., 1997). Personal initiative implies using productive, creative, and active strategies and overcoming problems if they occur and has been proposed as related to (corporate) entrepreneurship (Frese et al., 1996, 1997). Items from the seven-item scale ($\alpha = .79$) by Frese et

al. (1997) were measured on a five-point Likert-type scale (1 = *does not apply at all*, to 5 = *fully applies*). A sample item is “I actively attack problems.”

We also included age as a continuous control variable measured in years because younger individuals tend to be more adventurous and hence may have a greater willingness to engage in intrapreneurial activities (S. H. Lee & Wong, 2004). Finally, as women and men were found to differ in their rate of entrepreneurial entry (Autio et al., 2013), we controlled for sex (0 = *men*, 1 = *women*).

3.5 Results

Table 4 displays the descriptive statistics of the Level 2 variables. Mean test-retest reliabilities were .71 and .76 for employee corporate entrepreneurship participation likelihood and employee likelihood of intrapreneurial behavior, respectively, and were acceptable and comparable with other conjoint studies (e.g., Shepherd, 1999: .69 and Shepherd et al., 2003: .65). Following Aiman-Smith et al. (2002) and Cooksey (1996), we excluded the four replicated

Table 4

Descriptive Statistics of Level 2 Variables Used in Study 2

Variables	Mean	SD	1	2	3	4	5
1. Age	42.95	8.91					
2. Sex	0.20	0.40	-.09				
3. Willingness to take risks	3.35	0.65	-.22*	-.09			
4. Entrepreneurial experience	1.74	0.98	-.03	-.02	.13		
5. Personal initiative	4.09	0.50	-.07	.04	.08	-.06	
6. Intrapreneurial self-efficacy	3.85	0.56	-.00	.04	.14	.14	.65**

Note. $N = 85$. Sex is coded 0 = *male* and 1 = *female*.

* $p < .05$, ** $p < .01$

scenarios from further statistical analyses. Using 16 decisions per participant yielded 1,360 observations within 85 individuals. Thus, our sample size is in line with previously published conjoint studies (see, e.g., Drover et al., 2014; Shepherd et al., 2003). Due to the nested structure of our data, we applied multilevel regression analyses using SPSS 26. Level 1 refers to variables manipulated in the decision profiles, and Level 2 refers to the individual-level variables.

Following Glaser et al. (2016), we first ran null models for both dependent variables without any predictor to ensure sufficient variance between individuals. The ICC_1 values of employee corporate entrepreneurship participation likelihood and employee likelihood of intrapreneurial behavior were .10 and .16, respectively, which indicates that the variability between units was large and multilevel modeling was appropriate. Tables 5 and 6 display the results from our multilevel regression analyses for employee corporate entrepreneurship participation likelihood and employee likelihood of intrapreneurial behavior. We entered interactions in a step-wise manner into the model, a common method in multilevel studies testing multiple interactions (e.g., Hauswald et al., 2016), to minimize confounded effects. Moreover, even though it is difficult to estimate precise effect sizes in cross-level models, we report Snijders and Bosker's (1999) pseudo- R^2 .

In Model 1, only control variables (all Level 2) were entered. Results for employee corporate entrepreneurship participation likelihood showed that participation in corporate entrepreneurship endeavors was less likely for women ($b = -0.44, p = .02$) and for older employees ($b = -0.02, p = .06$; marginal significance). Results for employee likelihood of intrapreneurial behavior indicated that employees were more likely to engage in intrapreneurial behavior when they were male ($b = -0.74, p < .01$), showed a higher willingness to take risk ($b = 0.30, p = .02$), and demonstrated greater personal initiative ($b = 0.60, p < .01$).

In Model 2, we entered the independent variables manipulated in the conjoint profiles. We found statistically significant and positive effects of support by collaborative technologies ($b = 1.00, p < .01$), support by social media ($b = 0.46, p < .01$), and support by intelligent decision support systems ($b = 0.64, p < .01$) on employee corporate entrepreneurship participation likelihood. The relationships between support by collaborative technologies ($b = 0.96, p < .01$), support by social media ($b = 0.41, p < .01$), and support by intelligent decision support systems ($b = 0.63, p < .01$) on employee likelihood of intrapreneurial behavior were also statistically significant and positive. Thus, Hypotheses 1a, 1b, and 1c received support.

In Model 3, management support for innovation was entered. Management support for innovation was statistically significantly and positively related to both employee corporate entrepreneurship participation likelihood ($b = 2.38, p < .01$) and employee likelihood of intrapreneurial behavior ($b = 2.38, p < .01$). In Model 4, we entered intrapreneurial self-efficacy, which was statistically significantly and positively related to both employee corporate entrepreneurship participation likelihood ($b = 0.41, p = .02$) and employee likelihood of intrapreneurial behavior ($b = 0.46, p = .01$). In Model 5, the interaction effects between the digital technology support variables and management support for innovation proposed in Hypothesis 2 were added. Concerning employee corporate entrepreneurship participation likelihood, we found a statistically significant and positive interaction effect between support by collaborative technologies and management support for innovation ($b = 0.47, p < .01$). The interactions of management support for innovation with support by social media ($b = 0.08, p = .33$) as well as with support by intelligent decision support systems ($b = 0.03, p = .71$) were not statistically significant. With regard to employee likelihood of intrapreneurial behavior, however, we not only found a statistically significant and positive interaction of management support for innovation with support by collaborative technologies ($b = 0.47, p < .01$), but also with support by intelligent

decision support systems ($b = 0.19, p = .01$). The interaction of management support for innovation with support by social media ($b = 0.10, p = .18$) was not statistically significant. This provided support for Hypothesis 2a and partial support for Hypothesis 2c, while Hypothesis 2b did not receive support. We plotted all significant two-way interaction effects to facilitate interpretation (see Figure 3).

We entered the interaction effects between the digital technology support variables and intrapreneurial self-efficacy in Model 6. We found no statistically significant interactions of support by collaborative technologies ($b = 0.17, p = .22$), support by social media ($b = 0.14, p = .22$) and support by intelligent decision support systems ($b = -0.12, p = .25$) with intrapreneurial self-efficacy on employee corporate entrepreneurship participation likelihood. However, results showed statistically significant and positive interactions of support by collaborative technologies ($b = 0.28, p = .03$) and support by social media ($b = 0.31, p < .01$) with intrapreneurial self-efficacy on employee likelihood of intrapreneurial behavior. The interaction between support by intelligent decision support systems and intrapreneurial self-efficacy was not statistically significant ($b = 0.05, p = .66$). This provided partial support for Hypotheses 3a and 3b. Hypothesis 3c was not supported.

Table 5*Results From the Multilevel Analysis for Employee Corporate Entrepreneurship Participation Likelihood*

		Dependent variable: Employee corporate entrepreneurship participation likelihood													
		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
		<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>
	Intercept	4.20***	0.08	3.16***	0.12	1.93***	0.12	1.93***	0.13	2.08***	0.13	2.08***	0.13	2.08***	0.13
	Age	-0.02†	0.01	-0.02†	0.01	-0.02*	0.01	-0.02*	0.01	-0.02*	0.01	-0.02*	0.01	-0.02*	0.01
	Sex	-0.44*	0.19	-0.50*	0.21	-0.30	0.18	-0.31†	0.18	-0.31†	0.18	-0.31†	0.18	-0.31†	0.18
	Willingness to take risks	0.09	0.12	0.07	0.13	0.17	0.11	0.15	0.11	0.15	0.11	0.15	0.11	0.15	0.11
	Entrepreneurial experience	-0.01	0.08	-0.02	0.09	-0.02	0.07	-0.06	0.07	-0.06	0.07	-0.06	0.07	-0.06	0.07
	Personal initiative	0.25	0.15	0.26	0.17	0.23	0.14	-0.07	0.19	-0.07	0.19	-0.07	0.19	-0.07	0.19
H1a	Support by collaborative technologies (SCT)			1.00***	0.09	1.00***	0.08	1.00***	0.08	0.77***	0.09	0.77***	0.09	0.77***	0.09
H1b	Support by social media (SSM)			0.46***	0.09	0.46***	0.06	0.46***	0.06	0.42***	0.07	0.42***	0.07	0.42***	0.07
H1c	Support by intelligent decision support systems (IDS)			0.64***	0.09	0.64***	0.06	0.64***	0.06	0.63***	0.07	0.63***	0.07	0.63***	0.07
	Management support for innovation (MSI)					2.38***	0.11	2.38***	0.11	2.09***	0.13	2.09***	0.13	2.09***	0.13
	Intrapreneurial self-efficacy (ISE)							0.41*	0.17	0.41*	0.17	0.25	0.22	0.16	0.25
H2a	SCT x MSI									0.47***	0.08	0.47***	0.08	0.47***	0.08
H2b	SSM x MSI									0.08	0.08	0.08	0.08	0.08	0.08
H2c	IDS x MSI									0.03	0.08	0.03	0.08	0.03	0.08
H3a	SCT x ISE											0.17	0.14	0.30†	0.15
H3b	SSM x ISE											0.14	0.11	0.08	0.13
H3c	IDS x ISE											-0.12	0.11	-0.10	0.13
	MSI x ISE													0.18	0.24
H4a	SCT x MSI x ISE													-0.27†	0.14
H4b	SSM x MSI x ISE													0.11	0.14
H4c	IDS x MSI x ISE													-0.05	0.14
	Level 1 Pseudo <i>R</i> ²	.01		.14		.57		.57		.58		.58		.58	
	Level 2 Pseudo <i>R</i> ²	.09		.09		.09		.10		.10		.10		.10	

Note. *N* = 1,360 decisions nested within 85 individuals. Unstandardized coefficients are reported. Sex is coded 0 = *male* and 1 = *female*.

† *p* < .10, * *p* < .05, ** *p* < .01, *** *p* < .001

Table 6*Results From the Multilevel Analysis for Employee Likelihood of Intrapreneurial Behavior*

Dependent variable: Employee likelihood of intrapreneurial behavior															
		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
		<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>
	Intercept	3.85***	0.09	2.87***	0.11	1.68	0.12	1.69***	0.12	1.88***	0.12	1.88***	0.12	1.88***	0.12
	Age	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.01	0.01
	Sex	-0.74***	0.20	-0.83***	0.22	-0.85***	0.19	-0.88***	0.18	-0.88***	0.18	-0.88***	0.18	-0.88***	0.18
	Willingness to take risks	0.30*	0.13	0.20	0.14	0.26*	0.12	0.26*	0.12	0.26*	0.12	0.26*	0.12	0.26*	0.12
	Entrepreneurial experience	-0.02	0.08	-0.05	0.09	-0.02	0.08	-0.06	0.08	-0.06	0.08	-0.06	0.08	-0.06	0.08
	Personal initiative	0.60***	0.16	0.52**	0.18	0.60***	0.15	0.28	0.20	0.28	0.20	0.28	0.20	0.28	0.20
H1a	Support by collaborative technologies (SCT)			0.96***	0.09	0.96***	0.07	0.96***	0.07	0.73***	0.08	0.73***	0.08	0.73***	0.08
H1b	Support by social media (SSM)			0.41***	0.09	0.41***	0.07	0.41***	0.07	0.36***	0.08	0.36***	0.08	0.36***	0.07
H1c	Support by intelligent decision support systems (IDS)			0.63***	0.09	0.63***	0.06	0.63***	0.06	0.53***	0.07	0.53***	0.07	0.53***	0.07
	Management support for innovation (MSI)					2.38***	0.12	2.38***	0.12	2.00***	0.14	2.00***	0.14	2.00***	0.13
	Intrapreneurial self-efficacy (ISE)							0.46*	0.18	0.46*	0.18	0.09	0.21	0.01	0.24
H2a	SCT x MSI									0.47***	0.08	0.47***	0.08	0.47***	0.08
H2b	SSM x MSI									0.10	0.08	0.10	0.08	0.10	0.08
H2c	IDS x MSI									0.19*	0.08	0.19*	0.08	0.19*	0.08
H3a	SCT x ISE											0.28*	0.13	0.32*	0.15
H3b	SSM x ISE											0.31**	0.12	0.18	0.14
H3c	IDS x ISE											0.05	0.10	0.01	0.12
	MSI x ISE													0.19	0.24
H4a	SCT x MSI x ISE													-0.11	0.14
H4b	SSM x MSI x ISE													0.22	0.14
H4c	IDS x MSI x ISE													0.08	0.14
	Level 1 Pseudo <i>R</i> ²		.06		.17		.58		.59		.59		.60		.60
	Level 2 Pseudo <i>R</i> ²		.30		.30		.30		.32		.32		.32		.32

Note. $N = 1,360$ decisions nested within 85 individuals. Unstandardized coefficients are reported. Sex is coded 0 = *male* and 1 = *female*.

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Finally, in Model 7, we entered all possible two-way interactions (including the interaction between management support for innovation and intrapreneurial self-efficacy) to prevent biased estimates of the three-way interaction effects (Dawson & Richter, 2006) and three three-way interaction terms. The three-way interaction effect between support by collaborative technologies, management support for innovation, and intrapreneurial self-efficacy ($b = -0.27, p = .06$) on employee corporate entrepreneurship participation likelihood was marginally significant and negative, while the three-way interactions that involved support by social media ($b = 0.11, p = .42$) and support by intelligent decision support systems ($b = -0.05, p = .72$) did not reach common levels of statistical significance. The simple slope analysis for the marginally significant three-way interaction (see Figure 4) revealed that the interactive effect between support by collaborative technologies and management support for innovation was stronger in cases of low rather than high intrapreneurial self-efficacy, which corresponds with Hypothesis 4a. Regarding employee likelihood of intrapreneurial behavior, we found no statistically significant three-way interactions of support by collaborative technologies ($b = -0.11, p = .43$), support by social media ($b = 0.22, p = .11$), and support by intelligent decision support systems ($b = 0.08, p = .54$) with management support for innovation and intrapreneurial self-efficacy. Thus, Hypotheses 4b and 4c did not receive support, while Hypothesis 4a was partially supported.

As we found personal initiative and intrapreneurial self-efficacy to be statistically significantly correlated with $r = .65$, we also tested models excluding the control variable personal initiative as a robustness check to ensure that our results are not biased due to issues of multicollinearity. The results of our hypothesis testing did not change.

Figure 3

Two-Way Interaction Effects on Employee Corporate Entrepreneurship Participation Likelihood and Employee Likelihood of Intrapreneurial Behavior

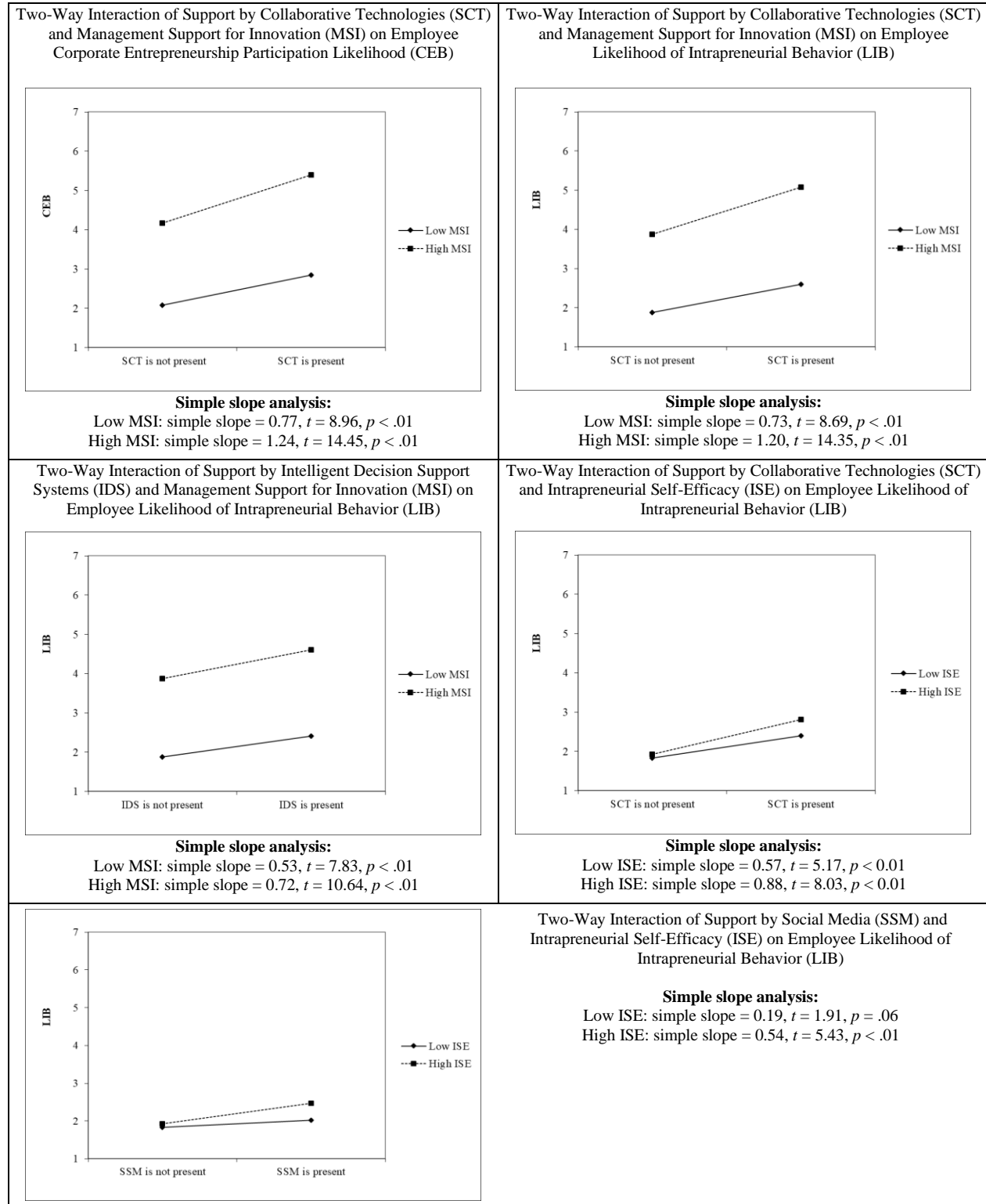
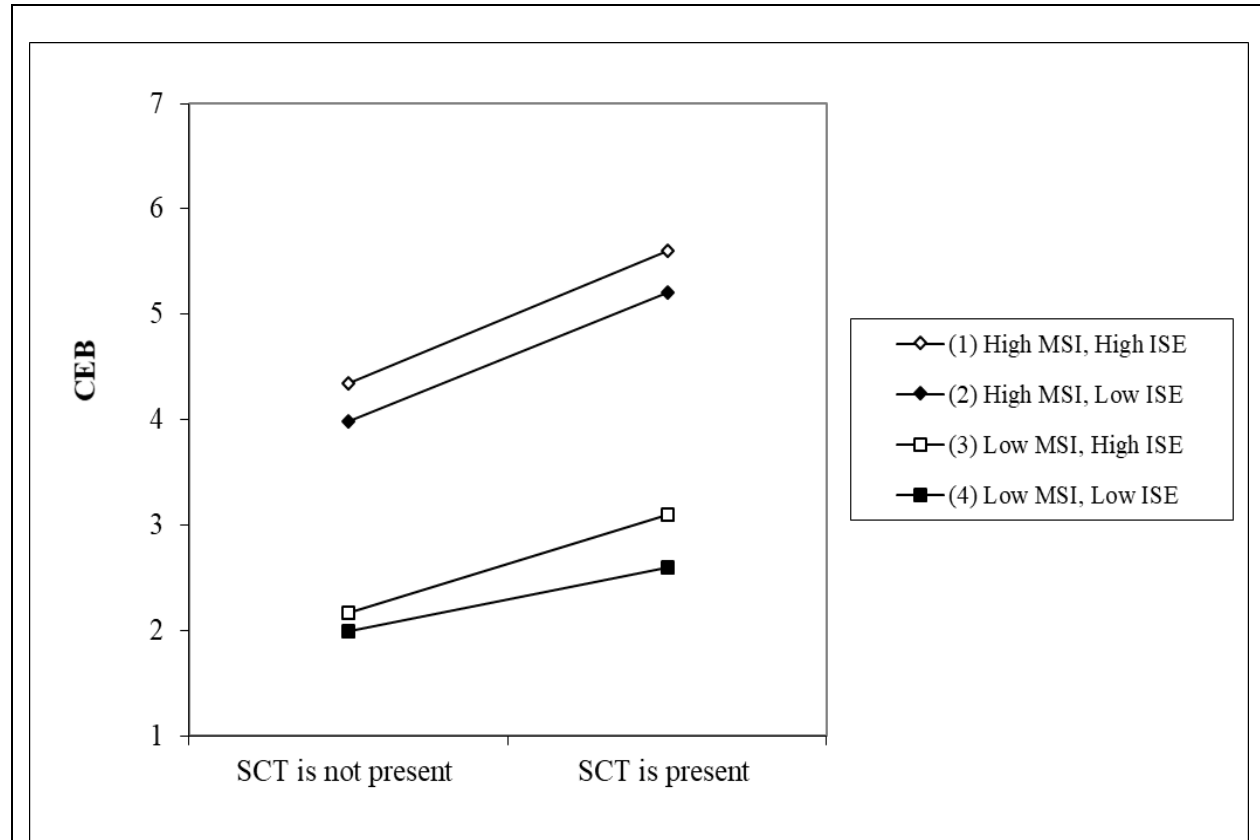


Figure 4

Three-Way Interaction Effect of Support by Collaborative Technologies (SCT), Management Support for Innovation (MSI), and Intrapreneurial Self-Efficacy (ISE) on Employee Corporate Entrepreneurship Participation Likelihood (CEB)



Simple slope analysis:

- (1) High MSI/High ISE: simple slope = 1.25, $t = 10.37$, $p < .01$
- (2) High MSI/Low ISE: simple slope = 1.22, $t = 10.11$, $p < .01$
- (3) Low MSI/High ISE: simple slope = 0.93, $t = 7.72$, $p < .01$
- (4) Low MSI/Low ISE: simple slope = 0.60, $t = 4.98$, $p < .01$

Slope difference tests:

Pair of slopes	t -value for slope difference	p -value for slope difference
(1) and (2)	0.19	.85
(1) and (3)	2.91	< .01
(1) and (4)	3.81	< .01
(2) and (3)	1.69	.09
(2) and (4)	5.62	< .01
(3) and (4)	1.94	.05

3.6 Discussion

3.6.1 Theoretical Implications

Drawing on the model of the corporate entrepreneurship process (Hornsby et al., 1993) and the conservation of resources theory (Hobfoll, 1989, 2001), our study examined the relationship between digital technology support and employee intrapreneurial behavior and how it is moderated by organizational (i.e., management support for innovation) as well as personal (i.e., intrapreneurial self-efficacy) resources. As predicted by conservation of resources theory, support by digital technologies (i.e., support by collaborative technologies, by social media, and by intelligent decision support systems) showed a significant positive effect on both employee corporate entrepreneurship participation likelihood and employee likelihood of intrapreneurial behavior. These results suggest that digital technology support reduces the resources necessary to perform intrapreneurial activities and leads to net resource gains for employees. This promotes our conservation of resources theorizing that digital technology support offers an opportunity to gain additional resources by engaging in intrapreneurial activities at a lower cost. Our findings indicate that digital technology support is another important factor of the internal organization environment that enhances employee intrapreneurial behavior and thus contribute to answering the call by Rigtering et al. (2019) to shed more light on internal organizational environment antecedents of employee intrapreneurial behavior.

Furthermore, our study contributes to the current discourse on how the organizational environment, and organizational resources, in particular, shape intrapreneurship. It does this by showing that management support for innovation is an important boundary condition for the effects of digital technology support. As we found management support for innovation had both direct and moderating effects, we move beyond previous studies that only suggested a direct

positive effect of this support (see, e.g., Hornsby et al., 2002). Specifically, we found that management support for innovation strengthened the positive relationship between support by collaborative technologies and both employee corporate entrepreneurship participation likelihood and employee likelihood of intrapreneurial behavior. It also strengthened the relationship between support by intelligent decision support systems and employee likelihood of intrapreneurial behavior.

With regard to personal resources, we found that the positive relationship between support by collaborative technologies and by social media on the one hand and employee likelihood of intrapreneurial behavior on the other hand was stronger in cases of high rather than low intrapreneurial self-efficacy. These findings, and those concerning the role of management support for innovation, provide support for the conservation of resources theorizing that a larger resource pool increases the likelihood that employees recognize the opportunity to gain additional resources through intrapreneurial activities at a lower cost when there is high support by digital technologies. Employees with more resources (i.e., additional organizational or personal resources at their disposal) seem to be more sensitive to opportunities as suggested by conservation of resources theory (Cropanzano & Wright, 2001; Hobfoll, 1989, Hobfoll & Shirom, 2001).

Although we found a significant interaction effect on employee likelihood of intrapreneurial behavior, management support for innovation did not moderate the effect of support by intelligent decision support systems on employee corporate entrepreneurship participation likelihood. This might be due to decision support appearing less important to employees just participating in a project rather than starting and leading one on their own accord. Thus, the impact of decision support might be less evident even when employees are provided with additional organizational resources. Furthermore, management support for innovation also

did not have a moderating effect on the relationship between support by social media and both operationalizations of employee intrapreneurial behavior. This could be because of social media's generativity (Malsbender et al., 2014). By making communication, problems, and ideas visible and commentable and thus enabling help from a large undirected community (Leonardi, 2014, Malsbender et al., 2014), social media democratize support. This, in turn, might cause management support for innovation to lose its importance with regard to changing the effect of digital technology support on employee intrapreneurial behavior.

Contrary to our expectations, we did not find intrapreneurial self-efficacy to moderate the relationship between digital technology support and employee corporate entrepreneurship participation likelihood. Thus, results revealed differences with regard to the role of intrapreneurial self-efficacy between mere participation in a corporate entrepreneurship project and starting such a project on one's own accord. Taking a conservation of resources theory view on our results, employees with a high intrapreneurial self-efficacy are more likely to recognize the opportunity to gain additional resources at a lower cost by initiating and advancing a corporate entrepreneurial project on one's own accord when there is support by collaborative technologies and social media. In contrast, intrapreneurial self-efficacy does not make a difference in recognizing the opportunity to gain additional resources at a lower cost through the mere participation in a corporate entrepreneurship project when there is support by digital technologies.

This could be due to employees with high intrapreneurial self-efficacy being people that have high confidence in their abilities to take the initiative to realize new products or services, to draw top management's attention to new opportunities, and to convince top management and colleagues of the feasibility of new ventures (Globocnik & Salomo, 2015). These are all particularly important abilities when initiating and advancing an intrapreneurial project on one's

own accord, but might be less relevant when just participating in an already planned intrapreneurial project. Thus, employees with high intrapreneurial self-efficacy might primarily recognize the opportunity that support by collaborative technologies and support by social media provide for convincing managers of their ideas. They may pay less attention to the advantages of digital technologies for just participating in a project. Collaborative technologies and social media are also tools that facilitate communication (Meroño-Cerdán et al., 2008; Treem & Leonardi, 2012) and make it easier to reach and convince others of ideas. However, intelligent decision support systems do not provide such functions. Hence, employees with a high intrapreneurial self-efficacy might not be particularly attentive to the opportunities that support by intelligent decision support systems provides for easier performing intrapreneurial activities. This explains why we did not find an interaction effect of support by intelligent decision support systems and intrapreneurial self-efficacy on employee likelihood of intrapreneurial behavior.

Contrary to our expectations, we could not find but one marginally significant three-way interaction. Thus, our results in part contradict Hornsby et al.'s (1993) model of the intrapreneurial process in organizations. The mostly insignificant three-way interactions indicate that the joint presence of the precipitating event (represented in our study by the availability of support by digital technologies), organizational characteristics, and individual characteristics is not necessary in every case for fostering intrapreneurial activities. However, findings suggest that organizational and personal resources could strengthen the triggering effect of the precipitating event. Moreover, the simple slope analysis of the marginally significant three-way interaction of support by collaborative technologies, management support for innovation, and intrapreneurial self-efficacy on employee corporate entrepreneurship participation likelihood revealed the interactive effect to be stronger in cases of low intrapreneurial self-efficacy. This provides at least

some support for Halbesleben et al.'s (2014) theorizing that resources could complement each other.

In sum, our findings contribute to the digital entrepreneurship and information systems literatures (e.g., Autio et al., 2018; Haarhaus et al., 2018) by providing empirical evidence that digital technologies might be not only drivers of entrepreneurship but also triggers of intrapreneurial activities. By examining the role of digital technology support and its interaction with organizational and personal resources, we were also able to respond to the call by Nambisan et al. (2017) to further explore the relationship between digital technologies and innovation.

3.6.2 Managerial Implications

Our findings show that investing in their digital-technology infrastructure can help organizations encourage intrapreneurial behavior. Organizations providing collaborative technologies, social media, and intelligent decision support systems can create an environment that supports and facilitates intrapreneurial activities.

Moreover, our results indicate that management support for innovation is an important determinant of employee intrapreneurial behavior. It is also an important supporting resource for encouraging participation in intrapreneurial activities and even more so in the initiation of those activities. Therefore, managers should show that they are aware of innovative employee ideas and encourage and reward the submission of ideas. They should also provide the necessary expertise and resources (e.g., money and time to launch new project ideas) to perform intrapreneurial activities and institutionalize those activities within the firm's systems and processes (Hornsby et al., 2002; Kuratko et al., 2005).

In addition, our findings show that intrapreneurial self-efficacy is an important factor for leveraging the potential of digital technology support, particularly when organizations aim to

encourage employees to initiate intrapreneurial activities. Thus, organizations should support the development of employee beliefs in their capabilities to perform intrapreneurial tasks, for example, through specific intrapreneurship training using action-learning approaches (J. Byrne et al., 2016). Additionally, when recruiting new employees, organizations are well-advised to pay specific attention to an applicant's self-efficacy and abilities with regard to performing intrapreneurship-related activities.

3.6.3 Limitations and Implications for Future Research

Our study has some limitations that could be avenues for future research. First, although we undertook several measures to ensure our conjoint scenario and manipulations were realistic, participants still had to decide based on four manipulated attributes. These measures included a supplementary study to ensure the practical relevance and external validity of our manipulations, asking participants to consider the project under current economic conditions, and informing them that except for the four manipulated conditions, the type and scope of the project would be comparable to those undertaken by their organization. However, in reality, participants would have access to more detailed information and would have more time to think through their decisions thoroughly (Holland & Garrett, 2015). Hence, future research might examine if our results remain stable in a real-world setting. Furthermore, in our conjoint experiment, participants were confronted with dichotomous digital technology support specifications (i.e., support is present or not present). However, examining real organizations would allow researchers to analyze the effect of different degrees of digital technology support.

Second, similar to other conjoint studies examining employee intrapreneurial behavior (see, e.g., Monsen et al., 2010), our study analyzes reactions based on a scenario typical of one specific type of an intrapreneurship project – an innovative project that might lead to a new

strategic business unit or an independent spin-off. However, intrapreneurial activities may not only take the form of venturing behavior but also the form of strategic renewal behavior (i.e., behavior that aims at enhancing an organization's ability to react to internal and external advancements; Gawke et al., 2017). It would thus be interesting for future research to explore how digital technology support affects employee strategic renewal behavior.

Third, in our study, we examined the moderating effect of one specific individual characteristic (intrapreneurial self-efficacy) that is associated with employee intrapreneurial behavior. However, when examining the relationship between digital technology support and employee intrapreneurial activities, it might also be interesting for future research to consider digital-technology-related characteristics such as digital-technology-related self-efficacy (Compeau & Higgins, 1995) or digital technology anxiety (Venkatesh, 2000).

Fourth, our sample includes employees working full-time in for-profit organizations in the German manufacturing sector. Research has shown that cultural differences affect an individual's assessment of the consequences of intrapreneurial activities (Hayton et al., 2002; Turró et al., 2014). Accordingly, culture might influence how employees perceive the resource gains and investments associated with intrapreneurial behavior (Gawke et al., 2018). Therefore, employees from different cultures might differ in their evaluation of the resource investments and possible resource gains associated with intrapreneurial behavior; they might not inevitably expect a net resource gain even when being supported by digital technologies. Future research might address this by conducting cross-cultural studies and comparing samples from different cultures.

4. The Relationship Between Digital Technology Characteristics and Employee Innovative Performance: The Mediating Role of Employee Techno-Work Engagement and Employee-Perceived Techno-Strain

4.1 Abstract

Based on the job demands-resources model, this chapter examines the mediating mechanisms in the relationships between the digital technology characteristics employee-perceived digital technology usefulness and employee-perceived digital technology complexity on the one hand and employee innovative performance on the other hand. Findings from a three-phase online survey study of 162 employees working in for-profit organizations in Germany show a statistically significant and positive indirect effect of employee-perceived digital technology usefulness on employee innovative performance via employee techno-work engagement. Contrary to expectations, results did not reveal a statistically significant indirect effect of employee-perceived complexity on employee innovative performance through employee-perceived techno-strain. However, the study found statistically significant and negative sequential indirect effects through either employee-perceived techno-strain or employee-perceived digital technology usefulness and employee techno-work engagement. Results indicate that digital technology characteristics reflecting digital-technology-related job resources and job demands play an important role in employee innovative performance by fostering employee motivation when working with digital technologies and inducing techno-strain perceptions.

Keywords: employee-perceived digital technology usefulness; employee-perceived digital technology complexity; employee techno-work engagement; employee-perceived techno-strain; employee innovative performance

4.2 Introduction

In our modern globalized economy, organizations have to face growing market challenges (Ardito et al., 2015) and increasingly complex and turbulent business environments (Hollen et al., 2013). Employee innovative behavior is important as a way for organizations to secure their competitive position and long-term survival in today's business landscape (Anderson et al., 2004, 2014) because it contributes to the continuous development of new products, services, and work processes (de Jong & den Hartog, 2010). Given the importance of employee innovative activities, organizations need to know the determinants of employee innovative performance to identify how they can promote it to gain a competitive advantage (Pieterse et al., 2010). *Employee innovative performance* refers to employees' production, adoption, and implementation of novel ideas (Bindl et al., 2019; Scott & Bruce, 1994; van de Ven, 1986).

Nowadays, organizations have to do business in a world increasingly permeated by digital technologies (Yoo et al., 2012). Digital technologies are defined as “products or services that are either embodied in information and communication technologies or enabled by them” (Lyytinen et al., 2016, p. 49). Considering the rapid digitalization and the rising significance of employee innovation, understanding how employee innovative activities can be fostered in increasingly digital settings is very important for organizations (Arthur, 2014; Korzynski et al., 2019). Digitalization and digital technologies have been theorized to be drivers of innovative activities (e.g., Nambisan et al., 2017; Yoo et al., 2012). However, studies on how the characteristics of digital infrastructures or digital technologies influence innovative activities are scarce; answering these questions seems merited (Nambisan et al., 2017).

The technology acceptance model and its extensions (see, e.g., Davis, 1989; Davis et al., 1989; Venkatesh & Bala, 2008; Venkatesh et al., 2003) propose that employees' positioning

toward the digital-technology infrastructure at their workplaces is particularly affected by the perceived usefulness and perceived complexity of digital technologies. Digital technologies are a resource for employees; they support flexibility and improve communication, collaboration, and access to information (J. R. Carlson et al., 2017; Day et al., 2010; Diaz et al., 2012). Thus, they are useful for employee-task accomplishment. However, digital technologies can also generate job demands. They are often complex and thus lead to continuous learning expectations, difficulties in understanding, and employees having to face hassles, interruptions, or complications (Day et al., 2012; Tarafdar et al., 2019). Hence, digital technologies and their characteristics may be a double-edged sword for employees. According to the job demands-resources model (Bakker & Demerouti, 2007, 2017; Demerouti et al., 2001), job resources foster work engagement, while job demands produce strain. Work engagement and strain both affect employee performance (Bakker & Demerouti, 2017). Hence, employee-perceived digital technology usefulness should lead to employee techno-work engagement. Similarly, employee-perceived digital technology complexity should result in the perception of techno-strain. Both should affect employees' innovative performance. Therefore, drawing on the job demands-resources model, I analyze how employee-perceived usefulness and complexity of the digital technologies at their workplace relate to their innovative performance. This is done by proposing two mediators: employee techno-work engagement as a mediator of the relationship between employee-perceived digital technology usefulness and employee innovative performance, and employee-perceived techno-strain as a mediator of the relationship between employee-perceived digital technology complexity and employee innovative performance.

This chapter provides several contributions. It answers Nambisan et al.'s (2017) call to more closely investigate the role of digital technologies and infrastructures in innovative processes and how they enable and constrain innovative activities. Although there is a growing body of literature

theorizing on these aspects (e.g., Kleinschmidt et al., 2016; Nambisan et al., 2017, 2019), research has predominately been conceptual and lacks empirical examinations. This study contributes to closing this gap. Concurrently, the paper responds to Braukmann et al.'s (2018) call to analyze the effects of using digital technology on individual performance. This is done by specifically examining the positive (i.e., employee techno-work engagement) and negative (i.e., employee-perceived techno-strain) processes that result from the characteristics of digital technologies. These characteristics potentially foster or hinder employee innovative performance. With this, the chapter also provides insights and guidance for managers on how to design their digital-technology infrastructure to be beneficial and not detrimental to employees' innovative performance.

Research has already found work engagement to positively stimulate performance outcomes (see, e.g., Bakker & Demerouti, 2017) and employee innovative behavior (e.g., Chang et al., 2013). However, although techno-work engagement is considered a specific type of work engagement, it is currently not known if it has similar positive effects as general work engagement (Mäkinen et al., 2020). Hence, this study answers Mäkinen et al.'s (2020) call for research on the outcomes of techno-work engagement. It analyzes the effects of employee-perceived techno-strain on employee techno-work engagement and thus investigates the relationship between negative aspects of digital technology usage and techno-work engagement. This aspect is still unclear according to Mäkinen et al. (2020); techno-work engagement is a novel construct and a specific version of work engagement, and not much is known about its determinants. I also contribute to knowledge in this area by examining employee-perceived digital technology usefulness as an antecedent of techno-work engagement. I introduce employee-perceived digital technology usefulness and complexity as digital-technology-related job resources and demands, respectively, and analyze their relationship with employee innovative performance. This extends the job demands-resources model literature. In doing so, I also contribute to the steadily growing

research on technology-related job demands and resources and the associated positive and negative consequences (e.g., J. R. Carlson et al., 2017; Day et al., 2010; Diaz et al., 2012; Kim & Christensen, 2017; Tarafdar et al., 2019).

4.3 Theory and Hypotheses

4.3.1 The Job Demands-Resources Model as a Theoretical Framework

The job demands-resources model distinguishes between two general sets of job characteristics that influence employees' motivation, strain, and finally, performance. These are job resources and job demands (Bakker & Demerouti, 2017; Schaufeli & Bakker, 2004). *Job resources* on the one hand can be defined as those physical, psychological, social, or organizational aspects of the job that are functional in achieving work goals, stimulate personal growth and development, or reduce job demands and the associated physiological and psychological costs (Bakker et al., 2004). On the other hand, *job demands* are “those physical, psychological, social, or organizational aspects of the job that require sustained physical and/or psychological (cognitive and emotional) effort or skills and are therefore associated with certain physiological and/or psychological costs” (Bakker & Demerouti, 2007, p. 312). Job demands and resources trigger two different psychological processes, a motivational process and a health-impairment process (Bakker & Demerouti, 2017).

In the motivational process, job resources are theorized to have a motivational potential that leads to high work engagement, which in turn fosters job performance (Bakker & Demerouti, 2007). Job resources are intrinsically motivating because they foster employee growth, learning, and development, and extrinsically motivating because they contribute to achieving work goals (Schaufeli & Bakker, 2004). Motivation and thus work engagement lead to improved job

performance because they foster goal orientation and focus on work tasks and provide employees with the energy and enthusiasm to perform well (Bakker & Demerouti, 2017).

In the health-impairment process, job demands are theorized to exhaust employees' mental and physical resources, reducing their energy and leading to strain, which negatively affects their performance (Bakker & Demerouti, 2007, 2017). High job demands cause strain because employees confronted with demanding work conditions tend to apply performance-protection strategies (Schaufeli & Bakker, 2004). These strategies are associated with compensatory costs that drain an employee's energy (Bakker & Demerouti, 2007; Hockey, 1997; Schaufeli & Bakker, 2004). Employees suffering from strain do not have the energy to reach their work goals, leading to reduced employee performance (Bakker & Demerouti, 2017; Bakker et al., 2004). In the job demands-resources model, strain fostered by job demands is also theorized to negatively affect employee work engagement because it triggers psychological withdrawal from work (Bakker, Demerouti, Taris, et al., 2003; Bakker et al., 2004).

4.3.2 Employee Techno-Work Engagement as a Mediator Between Employee-Perceived Digital Technology Usefulness and Employee Innovative Performance

Employee-perceived digital technology usefulness refers to the degree to which an employee believes that using a particular digital technology will enhance his or her job performance (Davis, 1989). In improving employees' job performance, useful digital technologies can be viewed as a job resource because they are functional in achieving work goals (Bakker & Demerouti, 2007). According to the job demands-resources model, job resources promote employee work engagement (Bakker & Demerouti, 2007, 2017). As a digital-technology-related job resource, employee-perceived digital technology usefulness might lead to employee techno-work engagement. *Employee techno-work engagement* is defined as "a positive and fulfilling well-being

state or experience that is characterized by vigor, dedication, and absorption with respect to the use of technology at work” (Mäkineniemi et al., 2020, p. 2). *Vigor* is characterized by high levels of energy, mental resilience, and persistence, and a willingness to spend effort on work. *Dedication* is associated with a sense of significance, enthusiasm, inspiration, pride, and challenge. Finally, *absorption* refers to being fully concentrated and deeply immersed in one’s work (Schaufeli et al., 2002). Thus, techno-work engagement is considered a positive motivational state towards the use of digital technologies at work (Larjovuori et al., 2016; Mäkineniemi et al., 2019).

As the productivity gains promised by working with useful digital technologies are beneficial for achieving work goals (Bakker & Demerouti, 2007; Davis et al., 1992), useful digital technologies have positive motivational consequences (Davis et al., 1992). Extrinsic motivational factors encourage an activity because they are perceived to be instrumental in achieving valued outcomes (Teo et al., 1999). When employees perceive that digital technologies are useful, they expect these technologies to have positive consequences for their task performance (Davis, 1989; Davis et al., 1989). Therefore, digital technologies that are perceived as useful are examples of such extrinsically motivating factors (Davis et al., 1992). As humans have the tendency to subconsciously pursue instrumental behaviors, useful digital technologies are positively related to employees’ persistence in using digital technologies (Bhattacharjee, 2001), which is an important aspect of employee vigor (Schaufeli et al., 2002). Extrinsically motivating factors have the potential to positively affect an individual’s enthusiasm about performing an activity (Serin, 2018). Thus, as such an extrinsically motivating factor, employee-perceived digital technology usefulness should spark the enthusiasm, and consequently the dedication of employees to using the digital technologies at their workplaces (Schaufeli et al., 2002). The perceived usefulness of digital technologies has been found to be positively correlated to employee concentration when using them (S. H. Liu et al., 2009; Y. Liu & Li, 2011). Hence, this usefulness should also be positively related

to employee absorption during the use of digital technologies in the workplace (Schaufeli et al., 2002).

When employees are in a state of high techno-work engagement, they perceive the use of the digital technologies at their workplace to be inspiring and feel energetic, happy, and immersed when they use them. These feelings are closely related to being in a state of flow (Larjovuori et al., 2016). Their perceived usefulness has, in turn, been found to be an antecedent of flow experiences when using digital technologies (Ahmad & Abdulkarim, 2019). The assumption is that, as a digital-technology-related job resource, employee-perceived digital technology usefulness induces employee techno-work engagement. This is in line with previous research by Mäkineniemi et al. (2019). They found positive relationships between other digital-technology-related job resources (i.e., technology-related autonomy and technology-related competence support) on the one hand and techno-work engagement on the other hand.

The job demands-resources model theorizes employee performance to be positively affected by employee motivation, engagement, and consequently techno-work engagement. Work engagement, and hence, techno-work engagement, is characterized by a high level of energy (Schaufeli & Bakker, 2010). Employees in a state of high techno-work engagement should have an energetic and affective connection with using the digital technologies at their workplace (Gorgievski et al., 2014; Mäkineniemi et al., 2020). These high energy levels are necessary for the self-regulatory, goal-oriented, and persistent aspects of proactively creating, promoting, or implementing ideas (Fritz & Sonnentag, 2009). Furthermore, in view of today's pervasive digitalization, digital technologies have a large influence on the innovation process (Lyytinen et al., 2016; Nambisan et al., 2017). Digital technologies allow the direct exchange of information and knowledge and facilitate reaching decision-makers (Černe et al., 2013). They thus play an important role in the development, promotion, and realization of ideas, and hence, for employee

innovative activities (Janssen, 2000). Given the important role of digital technologies for innovation and that innovative behavior by employees is largely a motivational issue (Amabile, 1988; Pieterse et al., 2010), employees' innovative performance should be positively affected when the use of digital technologies is motivating and energizing (Larjovuori et al., 2016). Being happy and immersed when using digital technologies has been found to foster idea creation (Yan et al., 2013). Since it fosters employee techno-work engagement, employee-perceived digital technology usefulness should indirectly affect their innovative performance. Thus:

Hypothesis 1: Employee techno-work engagement mediates the relationship between employee-perceived digital technology usefulness and employee innovative performance such that the indirect effect is positive.

4.3.3 Employee-Perceived Techno-Strain as a Mediator Between Employee-Perceived Digital Technology Complexity and Employee Innovative Performance

Employee-perceived digital technology complexity can be defined as the degree to which the use of a digital technology is free of effort (Ayyagari et al., 2011). As the use of complex digital technologies requires employees to invest effort and time and develop new skills (Ayyagari et al., 2011; Tarafdar et al., 2015), these technologies can be viewed as job demands. Thus, according to the job demands-resources model (Bakker & Demerouti, 2007, 2017), employee-perceived digital technology complexity, as a job demand, should have negative effects on employee energies and health, leading to exhaustion and strain. Techno-stress research has theorized and found techno-stress creators such as employee-perceived digital technology complexity to be determinants of perceived techno-strain (Tarafdar et al., 2010). *Employee-perceived techno-strain* can be defined as the behavioral, psychological, and physiological outcomes of techno-stress that are observed in individuals (Cooper et al., 2001; Kahn & Byosiene 1992; Ragu-Nathan et al., 2008).

Employee-perceived digital technology complexity results in techno-strain for several reasons. When employees have to face complex digital technologies, they are forced to spend time and effort in understanding how to use them (Tarafdar et al., 2010). These complex technologies threaten employees with a loss of control over the digital infrastructure at their workplace, their work, and themselves, which disrupts their state of constancy (Ayyagari et al., 2011; Chandra et al., 2019). Moreover, complex digital technologies can result in frustration, an example of psychological strain (Newton & Keenan, 1990). On the one hand, employees may lose track of the different features that complex digital technologies provide (Ayyagari et al., 2011). On the other hand, when employees fail to develop the new skills required for using complex digital technologies and unsuccessfully apply their existing knowledge to these new complex digital technologies, initial errors or knowledge gaps are transmitted, and their effects magnified (Tarafdar et al., 2010). Additionally, working with complex digital technologies can result in a higher employee workload (Day et al., 2010; Ragu-Nathan et al., 2008) because learning how to use these technologies is often performed to the detriment of other tasks, increasing employees' work burden (Ayyagari et al., 2011; Tarafdar et al., 2010). Work overload is a source of techno-strain (Ayyagari et al., 2011).

According to the job demands-resources model, strain and thus techno-strain has a negative impact on employee performance (Bakker & Demerouti, 2017). Employees that suffer from techno-strain feel drained, tired, and/or burned out from the activities that require them to use digital technologies (Ayyagari et al., 2011). Innovative activities require employees to invest substantial and demanding effort (Janssen, 2004). Techno-strained employees should thus be less likely to generate, promote, and realize innovative change. Additionally, employees that feel drained and exhausted from using digital technologies might become reluctant to use them (Fuglseth & Sørenbø, 2014). This could also harm innovative behavior because digital technologies

are the primary means of knowledge transfer and building social networks in organizations (Barber & Santuzzi, 2015).

Techno-strain might take the form of anxieties and low self-confidence when using digital technologies, which makes employees unable to be innovative at tasks that involve their use (Tarafdar et al., 2015). Given the large influence of digital technologies on the innovation process and their important role in innovative activities (Lyytinen et al., 2016; Nambisan et al., 2017), this should negatively affect employees' innovative performance. Moreover, previous research indicates that techno-strain might also manifest itself in lower levels of technology-enabled innovation (Tarafdar et al., 2015). Therefore, as it fosters employee-perceived techno-strain, employee-perceived digital technology complexity should indirectly affect employee innovative performance. Thus:

Hypothesis 2: Employee-perceived techno-strain mediates the relationship between employee-perceived digital technology complexity and employee innovative performance such that the indirect effect is negative.

4.3.4 The Relationship Between Employee-Perceived Digital Technology Complexity and Employee-Perceived Digital Technology Usefulness

The job demands-resources model proposes that there is a negative correlation between job demands and job resources (e.g., Bakker & Demerouti, 2007; Bakker, Demerouti, de Boer, & Schaufeli, 2003; Schaufeli & Bakker, 2004). This is in line with theoretical models from the digital technology literature, such as the technology acceptance model (Davis et al., 1989), which suggests a direct negative effect from employee-perceived complexity on employee-perceived usefulness. This is because increased complexity would impair instrumentality, which negatively affects

performance expectancies (Davis et al., 1989). Hence, a complex digital technology that is difficult and effort-intensive to use is less likely to be perceived as useful (Sánchez-Franco et al., 2013).

Furthermore, using complex digital technologies requires employees to invest effort in developing and learning new skills and how to use them successfully, which is something employees are reluctant to do and happens at the expense of dealing with other organizational tasks (Ayyagari et al., 2011; Tarafdar et al., 2010). This might have adverse consequences for perceptions of usefulness. Viewed from a different angle, the effort saved due to reduced complexity could be redeployed, allowing an employee to accomplish more work for the same effort and increasing perceptions of the digital technology's usefulness (Davis et al., 1989). This is supported by previous research, which found a negative relationship between perceived complexity and perceived usefulness in the context of clinical technologies (Heinlen et al., 2019) and microcomputer usage (Igbaria et al., 1996). This is also in line with research applying the technology acceptance model that found perceived ease of use, the degree to which an employee believes that using a particular digital technology would be free of effort (Davis, 1989) and hence the opposite of perceived digital technology complexity, to be positively related to perceived usefulness (e.g., van der Heijden, 2004; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Thus:

Hypothesis 3: Employee-perceived digital technology complexity is negatively related to employee-perceived digital technology usefulness.

4.3.5 The Relationship Between Employee-Perceived Techno-Strain and Employee Techno-Work Engagement

The job demands-resources model posits that strain negatively affects employee work engagement (Bakker & Demerouti, 2017). The components of techno-work engagement, *techno-vigor* (energy and enthusiasm on using the digital technologies at one's workplace), *techno-*

dedication (perseverance and resiliency when using the digital technologies at one's workplace), and *techno-absorption* (immersion in using the digital technologies at one's workplace), all require sustained attention, higher-level reasoning, effort exertion, and impulse control and thus a high amount of energy (Barber et al., 2013). When facing technology-induced exhaustion, employees tend to adopt a defensive posture to defend their remaining energy resources (Barber et al., 2013; Hobfoll, 1989). Consequently, this would impair employee techno-work engagement because employees would be reluctant to spend additional energy.

Furthermore, techno-strain might lead to employees' psychological withdrawal (Bakker, Demerouti, Taris, et al., 2003), which leads to disengagement (Bakker et al., 2004), and hence may negatively affect employee techno-work engagement. Similarly, when employees distance themselves psychologically from work due to techno-strain (Taris et al., 2001), they should be less likely to be in a state of vigor, dedication, and absorption when working with digital technologies. Moreover, techno-work engagement is characterized as a positive and fulfilling well-being state (Mäkinen et al., 2020). Strain, in turn, is negatively related to employee well-being (Maggiori et al., 2013). In sum, employees should be less engaged when using the digital technologies at their workplace when they feel strained, fatigued, and exhausted due to their activities involving those digital technologies (Zacher & Winter, 2011). This is supported by previous research that found employee-perceived strain and employee work engagement to be negatively correlated (Brough et al., 2013; Schmitt et al., 2016). Thus:

Hypothesis 4: Employee-perceived techno-strain is negatively related to employee techno-work engagement.

4.4 Method

4.4.1 Sample and Procedures

To empirically test my hypotheses, I conducted a three-phase online study. Variables were assessed at three different points in time (employee-perceived digital technology usefulness and employee-perceived digital technology complexity as well as control variables in Phase 1, employee techno-work engagement and employee-perceived techno-strain in Phase 2, and employee innovative performance in Phase 3) to reduce the possibility of common method bias (Podsakoff et al., 2003). Employees that worked in German for-profit organizations were invited to participate in the study. They were recruited via personal networks and the professional network service Xing, Germany's biggest business network (Hofeditz et al., 2017). This recruitment method increased the heterogeneity of the sample and thus the generalizability of my findings (Demerouti & Rispens, 2014). In total, 304 individuals agreed to take part in the study and were sent an e-mail invitation that contained the link to the Phase 1 survey. Individual phases were separated by approximately one week (for similar approaches, see, e.g., Ferris et al., 2015; Lian et al., 2012; Pundt & Venz, 2017). Of the 304 invited employees, 259 provided complete answers to the Phase 1 questionnaire (85.20% response rate), 244 to the Phase 2 questionnaire (94.21% response rate from Phase 1, 80.26% overall response rate), and 236 participants completed the three surveys (91.12% response rate from Phase 1, 96.72% response rate from Phase 2, and 77.63% overall response rate). Respondents were asked to create an eight-digit code to match their answers for all three phases. For each participant who finished all three phases, fifty cents were donated to charity. As an additional incentive, participants were given the option to receive a short summary of the study's main results. Of those who responded, 22 had to be

excluded from the analysis because their codes did not match, and 52 because they did not meet the sampling criteria.

Thus, the final sample included 162 participants, with 55.56% being female. The average participant was 38.34 years old ($SD = 11.25$; $MIN = 24$ years; $MAX = 65$ years), had 15.86 years of working experience ($SD = 13.09$; $MIN < 6$ months; $MAX = 50$ years), and had a job tenure of 7.57 years ($SD = 9.21$; $MIN < 6$ months; $MAX = 43$ years). Participants were employed in various industries. In the sample, 61.73% held a university (or comparable) degree, and 3.70% had a Ph.D. Among them, 30.25% had a leadership position in their organization, 5.56% were blue-collar workers, and 12.35% were in part-time employment. Regarding hierarchy level, 42.59% held operational positions, 29.63% lower-management positions, 15.43% middle-management positions, 11.73% upper-management positions, and 0.62% top-management positions. To test for nonresponse bias, non-respondents were compared to the participants in the final sample regarding their sex. However, the χ^2 -test was not statistically significant ($\chi^2 = 0.63$, $p = .43$).

4.4.2 Measures

To measure the study variables, suitable and reliable scales and items from previously validated instruments were selected. Scales for which no validated German versions existed were translated using a bilingual committee approach in combination with pretest procedures (Brislin, 1970; S. P. Douglas & Craig, 2007). If not stated otherwise, participants were asked to indicate their level of agreement on a five-point Likert-type scale (1 = *strongly disagree* to 5 = *strongly agree*).

4.4.2.1 Phase 1 Variables

Employee-perceived digital technology usefulness ($\alpha = .95$) was measured by drawing on a six-item scale from Davis (1989). It was adapted to refer to the digital technologies at the respondent's workplace instead of the specific software "Chart-Master". A sample item is "The digital technologies at my workplace enable me to accomplish tasks more quickly."

Following Ayyagari et al. (2011), I measured employee-perceived digital technology complexity ($\alpha = .78$) by using the three-item scale from G. C. Moore and Benbasat (1991). Originally measuring the perceived ease of use of personal work-stations, the scale was modified to refer to the digital technologies at the participant's workplace. A sample item is "Learning to use the digital technologies at my workplace was easy for me." Items were reverse coded in the analysis to reflect the perceived complexity.

I also assessed several control variables. Previous research suggests that the demographic background of employees might account for the variance in their innovative activities (Newman et al., 2018). I controlled for age (measured as continuous variable) and sex (0 = *men*, 1 = *women*⁵). As part-time workers tend to contribute less to the organization (Stamper & Van Dyne, 2001) and thus might be less likely to perform extra-role behavior such as innovative activities, I also controlled for full-time/part-time employment (0 = *full-time employment*, 1 = *part-time employment*). Finally, I controlled for management support for innovation ($\alpha = .85$). This support has been theorized (Hornsby et al., 2002) and found to be an antecedent of employee innovative activities (Riaz et al., 2018). It was measured with a German translation (Engelen et al., 2015) of the five-item scale from Hornsby et al. (2013). A sample item is "Those employees who come up with innovative ideas on their own often receive management encouragement for their activities."

⁵ The final sample did not contain any participants that identified themselves as "diverse."

A confirmatory factor analysis using MPlus (Version 8.4) was conducted to check for discriminant validity. A three-factor solution (perceived usefulness, perceived complexity, and management support for innovation) fitted the data well ($\chi^2 = 114.37$, $df = 74$, $p < .01$, CFI = .97, TLI = .97, RMSEA = .06, SRMR = .07). A two-factor model in which the items of the two digital technology characteristics loaded onto one single factor had a statistically significantly worse fit ($\chi^2 = 215.13$, $df = 76$, $p < .01$, CFI = .90, TLI = .88, RMSEA = .11, SRMR = .08; $\Delta \chi^2 = 100.76$, $\Delta df = 2$, $p < .01$). To detect whether the Phase 1 variables were affected by common method variance, I tested a one-factor solution as an additional alternative model, which had a statistically significantly worse fit ($\chi^2 = 505.48$, $df = 77$, $p < .01$, CFI = .70, TLI = .64, RMSEA = .19, SRMR = .16; $\Delta \chi^2 = 391.11$, $\Delta df = 3$, $p < .01$). This gives the first hint that common method variance might not be a large problem for the Phase 1 variables (Korsgaard & Roberson, 1995; Mossholder et al., 1998; Podsakoff et al., 2003). However, to perform a more detailed check for common method bias, I followed the recommendations of Lindell and Whitney (2001) and conducted a confirmatory factor analysis with *faith in intuition* measured in Phase 1 as a marker variable. This refers to “people's reliance on their intuition when making judgments or decisions” (Schindler et al., 2020, p. 1). Faith in intuition ($\alpha = .75$) was assessed with Keller et al.'s (2000) German translation of Epstein et al.'s (1996) five-item scale. The model with the marker variable had a statistically significantly worse fit than the three-factor solution ($\chi^2 = 224.00$, $df = 136$, $p < .01$, CFI = .95, TLI = .93, RMSEA = .06, SRMR = .18; $\Delta \chi^2 = 109.63$, $\Delta df = 62$, $p < .01$). Moreover, the comparison between the standardized factor loadings of the model with the marker variable and the original model revealed only small differences (differences are zero when rounding to two decimal places). These were thus below the threshold of .20 commonly used to detect common method bias (see, e.g., Doluca et al., 2018; Simon & Tossan, 2018). Hence, it can be assumed that common method variance might not affect Phase 1 variables.

4.4.2.2 Phase 2 Variables

Following Mäkineniemi et al. (2020), employee techno-work engagement was modeled as a reflective second-order construct composed of the three first-order reflective constructs employee techno-vigor, employee techno-dedication and employee techno-absorption. All three first-order constructs were measured by the three-item scales developed by Mäkineniemi et al. (2020) and were slightly modified to reflect employees' vigor, dedication, and absorption when using the digital technologies at their workplaces instead of using technology in their jobs. A sample item for employee techno-vigor ($\alpha = .80$) is "When I utilize the digital technologies at my workplace, I feel that I am bursting with energy." A sample item for employee techno-dedication ($\alpha = .85$) is "I am enthusiastic about utilizing the digital technologies at my workplace." Finally, a sample item for employee techno-absorption ($\alpha = .87$) is "I feel happy when I am immersed in using the digital technologies at my workplace."

Employee-perceived techno-strain ($\alpha = .89$) was assessed using Ayyagari et al.'s (2011) adaption of the four-item scale of J. E. Moore (2000). It was modified to capture the perceived strain resulting from respondents using the digital technologies at their workplaces rather than that stemming from their activities involving information and communication technologies. A sample item is "I feel burned out from using the digital technologies at my workplace."

A confirmatory factor analysis using MPlus (Version 8.4) was conducted to check for discriminant validity. The solution with employee techno-work engagement modeled as a second-order construct and employee-perceived techno-strain as a first-order construct fitted the data well ($\chi^2 = 97.38$, $df = 61$, $p < .01$, CFI = .97, TLI = .97, RMSEA = .06, SRMR = .06). A two-factor model in which all items of the three first-order constructs measuring employee techno-work engagement loaded onto one single factor had a significantly worse fit ($\chi^2 = 242.14$,

$df = 64$, $p < .01$, CFI = .87, TLI = .84, RMSEA = .13, SRMR = .07; $\Delta \chi^2 = 144.76$, $\Delta df = 3$, $p < .01$). To test for common method bias, I again tested a model in which all items loaded onto one factor. It had a statistically significantly worse fit ($\chi^2 = 556.33$, $df = 65$, $p < .01$, CFI = .63, TLI = .55, RMSEA = .22, SRMR = .15; $\Delta \chi^2 = 458.95$, $\Delta df = 4$, $p < .01$) than the original model. Additionally, a confirmatory factor analysis with faith in intuition measured in Phase 2 ($\alpha = .72$) as a marker variable revealed a statistically significantly worse fit for the model with the marker variable included ($\chi^2 = 250.19$, $df = 119$, $p < .01$, CFI = .92, TLI = .89, RMSEA = .08, SRMR = .20; $\Delta \chi^2 = 152.81$, $\Delta df = 58$, $p < .01$). Comparing the standardized factor loadings of the model with the marker variable to the factor loadings in the original model showed differences of .05 and less. This is below the threshold of .20. Hence, common method variance might not affect Phase 2 variables.

4.4.2.3 Phase 3 Variables

In line with previous research (e.g., Janssen, 2001), employee innovative performance ($\alpha = .93$) was measured by using the German version (Hardt, 2011) of the nine-item scale from Janssen (2000). The items had to be rated on a five-point Likert-type scale (1 = *never* to 5 = *always*). A sample item is “In your job, how often do you create new ideas for difficult issues?”

I chose self-reported measures instead of observer-scores for several reasons. Peers or supervisors do not necessarily have a more accurate picture of their colleagues' or subordinates' innovative activities than they do of themselves (Axtell et al., 2000). Employees have much more information about the historical, contextual, intentional, and other backgrounds of their own work activities. Thus, their reports of their innovative performance are likely to be more subtle than those of their colleagues or supervisors (Janssen, 2000; Jones & Nisbett, 1971). Moreover, being highly susceptible to idiosyncratic interpretations, employee innovative performance might vary across

different raters (Janssen, 2000; Organ & Konovsky, 1989). Furthermore, employees might be better positioned than supervisors or colleagues at judging whether new work ideas are fundamentally or incrementally innovative (Ng & Feldman, 2013). Finally, there is the possibility that a supervisor-based measure could miss much genuine employee innovative activities and capture only those gestures intended to impress the supervisor (Janssen, 2000; Organ & Konovsky, 1989).

I also conducted a confirmatory factor analysis using MPlus (Version 8.4) for the measurement model for employee innovative performance. The fit with the data was acceptable ($\chi^2 = 94.81$, $df = 27$, $p < .01$, CFI = .93, TLI = .91, RMSEA = .13, SRMR = .05). As employee innovative performance was the only variable measured in Phase 3, a test for common method bias was not necessary.

4.4.3 Data Analysis

All hypotheses were tested using structural equation modeling techniques with MPlus (Version 8.4). However, to use these techniques with multiple manifest indicators, minimum sample sizes of 180 (for small mediation models; Wolf et al., 2013) or 200 (e.g., Boomsma & Hoogland, 2001; B. O. Muthén & Asparouhov, 2015) are recommended in the literature. Thus, I generated latent variables by using the composite scale of each first-order construct as the single indicator and corrected for measurement unreliability by applying the approach suggested by Schumacker and Lomax (2010). The latter allowed me to avoid substantially under- or over-estimating the path coefficients and generating biased results (Cole & Preacher, 2014; Wolf et al., 2013). This procedure requires fewer participants than equivalent full-measurement models (Wolf et al., 2013). Following Preacher and Hayes (2008), bootstrapping analyses were performed to test the mediation hypotheses and indirect effects with a bootstrapping sample of 5,000. Following common practice, significance decisions for the direct effects were made based

on p -values (Montoya & Hayes, 2017). To account for the often-asymmetric sampling distribution of the indirect effects, significance decisions concerning the mediation hypotheses were made using bootstrap confidence intervals (Preacher & Hayes, 2008).

4.5 Results

4.5.1 Hypothesis Testing

Table 7 shows descriptive statistics and correlations for all study variables. The structural model results are set out in Table 8 (results of control-variable testing) and Table 9 (path and mediation results for the focal variables). In the structural model, the control variables age, sex, and full-time/part-time employment did not have statistically significant relationships with employee techno-work engagement and employee innovative performance. Furthermore, while full-time/part-time employment was not statistically significantly related to employee-perceived techno-strain, being a woman was found to have a statistically significant and positive relationship with employee-perceived techno-strain ($\beta = .18, p = .02$). Moreover, age was statistically marginally significantly and positively related to employee-perceived techno-strain ($\beta = .16, p = .06$). Finally, management support for innovation was statistically significantly and positively related to employee innovative performance ($\beta = .20, p = .01$).

Table 7*Descriptive Statistics and Correlations of Study 3 Variables*

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10
1. Age	38.34	11.25										
2. Sex	0.56	0.50	-.17*									
3. Full-time/part-time employment	0.12	0.33	.25**	.30**								
4. Management support for innovation	2.68	0.85	-.12	-.03	-.05							
5. Employee-perceived digital technology usefulness	3.97	0.82	-.04	-.17*	-.09	.24**						
6. Employee-perceived digital technology complexity	2.04	0.73	.24**	-.10	.06	-.06	-.35**					
7. Employee techno-vigor	3.51	0.82	-.07	-.09	-.10	.08	.19*	-.24**				
8. Employee techno-dedication	3.47	0.89	-.04	-.07	-.07	.06	.29**	-.17*	.65**			
9. Employee techno-absorption	2.95	0.92	-.11	.00	-.06	.06	.17*	-.25**	.59**	.68**		
10. Employee-perceived techno-strain	1.84	0.73	.17*	.09	.03	-.02	-.19*	.30**	-.41**	-.27**	-.24**	
11. Employee innovative performance	2.91	0.73	.00	-.03	-.07	.18*	.03	-.14	.32**	.18*	.24**	-.20*

Note. $N = 162$. Sex is coded 0 = men and 1 = women. Full-time/part-time employment is coded 0 = full-time and 1 = part-time.

* $p < .05$, ** $p < .01$

In line with Hypothesis 1, a statistically significant and positive indirect effect of employee-perceived digital technology usefulness ($\beta = .05$, $SE = .04$, $CI = [0.00^6, 0.14]$) on employee innovative performance via employee techno-work engagement was found. Both the direct effect of employee-perceived digital technology usefulness ($\beta = .21$, $p = .02$) on employee techno-work engagement and the direct effect of employee techno-work engagement on employee innovative performance ($\beta = .26$, $p = .03$) were statistically significant and positive.

The indirect effect of employee-perceived digital technology complexity ($\beta = -.04$, $SE = .04$, $CI = [-0.12, 0.04]$) on employee innovative performance through employee-perceived techno-strain was not statistically significant. Thus, Hypothesis 2 did not receive support. The direct relationship of employee-perceived digital technology complexity and employee-perceived techno-strain was statistically significant and positive ($\beta = .36$, $p < .01$). However, the direct relationship between employee-perceived techno-strain and employee innovative performance was not statistically significant ($\beta = -.11$, $p = .29$).

Results revealed the relationship between employee-perceived digital technology complexity and employee-perceived digital technology usefulness to be statistically significant and negative ($\beta = -.42$, $p < .01$). Consequently, Hypothesis 3 received support. In line with Hypothesis 4, the relationship between employee-perceived techno-strain and employee techno-work engagement was also found to be statistically significant and negative ($\beta = -.36$, $p < .01$).

⁶ The lower bound is 0.00 due to rounding to two decimal places, the value is greater than zero.

Table 8*Structural Model Results of Study 3: Control Variables*

Path	β	<i>SE</i>	<i>p</i>
Age → Employee techno-work engagement	.02	.09	.85
Sex → Employee techno-work engagement	.03	.09	.77
Full-time/part-time employment → Employee techno-work engagement	-.08	.08	.37
Age → Employee-perceived techno-strain	.16	.09	.06
Sex → Employee-perceived techno-strain	.18	.08	.02
Full-time/part-time employment → Employee-perceived techno-strain	-.09	.10	.38
Age → Employee innovative performance	.10	.08	.21
Sex → Employee innovative performance	-.00 ^a	.08	.98
Full-time/part-time employment → Employee innovative performance	-.07	.08	.42
Management support for innovation → Employee innovative performance	.20	.08	.01

Note. *N* = 162.^a -.00 due to rounding to two decimal places, the value is smaller than zero.

Table 9*Structural Model Results of Study 3: Focal Variables*

Path	β	<i>SE</i>	<i>p</i> / CI
<i>Second-order estimated paths</i>			
Employee techno-vigor → Employee techno-work engagement	.88	.05	< .01
Employee techno-dedication → Employee techno-work engagement	.91	.06	< .01
Employee techno-absorption → Employee techno-work engagement	.83	.06	< .01
<i>Indirect effects</i>			
H1: Employee-perceived digital technology usefulness → Employee techno-work engagement → Employee innovative performance	.05	.04	[0.00 ^a , 0.14]
H2: Employee-perceived digital technology complexity → Employee-perceived techno-strain → Employee innovative performance	-.04	.04	[-0.12, 0.04]
<i>Direct effects</i>			
Employee-perceived digital technology usefulness → Employee techno-work engagement	.21	.09	.02
Employee-perceived digital technology complexity → Employee-perceived techno-strain	.36	.09	< .01
Employee techno-work engagement → Employee innovative performance	.26	.12	.03
Employee-perceived techno-strain → Employee innovative performance	-.11	.10	.29
H3: Employee-perceived digital technology complexity → Employee-perceived digital technology usefulness	-.42	.08	< .01
H4: Employee-perceived techno-strain → Employee techno-work engagement	-.36	.09	< .01

Note. *N* = 162. Employee techno-vigor, employee techno-dedication, and employee techno-absorption are sub-dimensions of employee techno-work engagement. The *p*-values of indirect effects are not reported because significance decisions are made based on confidence intervals (Preacher & Hayes, 2008).

^a.00 due to rounding to two decimal places, the value is greater than zero.

4.5.2 Supplementary Analyses

To better understand the results and to shed additional light on the relationships among my focal variables, supplementary analyses were performed. The first two supplementary analyses were conducted to gain more insights on the determinants of employee techno-work engagement, a phenomenon for which there is scant research because of the concept's novelty. First, I examined whether employee-perceived digital technology complexity indirectly affected employee techno-work engagement via employee-perceived techno-strain. The indirect effect was statistically significant and negative ($\beta = -.13$, $SE = .05$, $CI = [-0.24, -0.05]$). Second, I tested whether employee-perceived digital technology complexity had an indirect effect on employee techno-work engagement via employee-perceived digital technology usefulness. This indirect effect was also statistically significant and negative ($\beta = -.09$, $SE = .04$, $CI = [-0.17, -0.01]$).

In a third supplementary analysis, to better understand why employee-perceived techno-strain did not affect employee innovative performance, I analyzed the indirect effect of employee-perceived techno-strain on employee innovative performance through employee techno-work engagement. It was statistically significant and negative ($\beta = -0.09$, $SE = .06$, $CI = [-0.24, -0.01]$). Thus, results indicate that employee-perceived techno-strain, by reducing employee motivation, is indirectly, rather than directly, related to employee innovative performance.

Fourth, building on supplementary analyses two and three, I tested for sequential mediation. I analyzed whether the relationship between employee-perceived digital technology complexity and employee innovative performance is sequentially mediated by employee-perceived techno-strain and employee techno-work engagement. The indirect effect ($\beta = -0.03$, $SE = .02$, $CI = [-0.10, -0.00^7]$) was statistically significant and negative. I also analyzed whether

⁷ The upper bound is 0.00 due to rounding to two decimal places, the value is smaller than zero.

the association between employee-perceived digital technology complexity and employee innovative performance is sequentially mediated by employee-perceived digital technology usefulness and employee techno-work engagement. Here, the indirect effect ($\beta = -0.02$, $SE = .02$, $CI = [-0.06, -0.00]$; see Footnote 7) was also statistically significant and negative.

Finally, I considered further arguments from the job demands-resources model (see, e.g., Bakker & Demerouti, 2007, 2017), which suggest job resources and demands interact with each other such that job resources buffer the negative effects of job demands and job resources and particularly influence work engagement when demands are high. These interactions depend on the specific context and characteristics of the job and its resources and demands (Bakker & Demerouti, 2007), and previous research on digital technologies (e.g., Davis et al., 1989) proposed direct effects rather than interactions. Interaction effects among job resources and demands were, therefore, not hypothesized directly. However, to examine if there might nonetheless be interactions, I tested whether employee-perceived digital technology usefulness (as a job resource) moderated the relationship of employee-perceived digital technology complexity with employee-perceived techno-strain and whether employee-perceived digital technology complexity (as a job demand) moderated the relationship between employee-perceived digital technology usefulness and employee techno-work engagement. The interactions of employee-perceived digital technology usefulness and employee-perceived digital technology complexity were not statistically significantly related to employee-perceived techno-strain ($\beta = .03$, $p = .85$) and employee techno-work engagement ($\beta = -.02$, $p = .86$).

4.6 Discussion

4.6.1 Theoretical Implications

Drawing on the job demands-resources model, this study aimed to resolve the question of how employee-perceived digital technology usefulness (as a digital-technology-related job resource) and employee-perceived digital technology complexity (as a digital-technology-related job demand) affect employee innovative performance via employee techno-work engagement and employee-perceived techno-strain, respectively. As predicted by the motivational path of the job demands-resources model (see Bakker & Demerouti, 2007, 2017), employee-perceived digital technology usefulness was found to have a statistically significant and positive indirect effect on employee innovative performance through employee techno-work engagement. Therefore, employee-perceived digital technology usefulness seems to induce techno-work engagement, which in turn positively affects employee innovative performance. By introducing and finding employee-perceived digital technology usefulness as an antecedent of employee techno-work engagement, I could advance research on the determinants of this novel construct (Mäkineniemi et al., 2020).

The results, which show a positive relationship between employee techno-work engagement and employee innovative performance, are in line with previous research theorizing and empirically examining employee work engagement as a factor that fosters employee performance (e.g., Bakker et al., 2012; Breevaart et al., 2015) and employee innovative activities (e.g., Chang et al., 2013; Gorgievski et al., 2014). The results here advance knowledge on employee techno-work engagement by revealing it to have similar positive effects as general work engagement (Mäkineniemi et al., 2020). In the supplementary analyses, I found that employee-perceived digital technology complexity and employee-perceived techno-strain only

affected employee innovative performance indirectly by reducing employee techno-work engagement. Consequently, it seems that employee motivation induced by dedicated work with the digital technologies at their workplace plays an important role in enhancing employee innovative performance.

Furthermore, I found employee-perceived digital technology complexity led to employee-perceived techno-strain, which corresponds with previous research on techno-stress (see, e.g., Tarafdar et al., 2010). However, results did not reveal employee-perceived techno-strain as affecting employees' innovative performance. Contrary to the predictions of the job demands-resources model and my expectations, results did not show that employee-perceived digital technology complexity indirectly affected their innovative performance through perceived techno-strain. Thus, findings are not fully in line with the health-impairment process proposed by the job demands-resources model (see Bakker & Demerouti, 2007, 2017).

However, as suggested by the job demands-resources model (Bakker & Demerouti, 2017), I found a significantly negative relationship between employee-perceived techno-strain and employee techno-work engagement. Considering the results from the supplementary analyses, it seems that perceiving techno-strain does not harm innovative performance directly but indirectly by lowering employee motivation while working with digital technologies. This corresponds with the findings from Bakker et al. (2004), which indicate that strain only affects employee extra-role performance by reducing work engagement. Results from the main and supplementary analyses respond to the call by Mäkinen et al. (2020) to shed more light on the relationship between the negative consequences of digital technology use and employee techno-work engagement and their influence on employee performance.

I found employee-perceived digital technology complexity to negatively affect employee-perceived digital technology usefulness, which is in line with the technology acceptance model

(Davis et al., 1992) and its extensions (Venkatesh, 2000; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Supplementary analyses also revealed that employee-perceived digital technology complexity was negatively related to employee techno-work engagement and employee innovative performance via employee-perceived digital technology usefulness. Thus, with finding that employee-perceived techno-strain does not impede employee innovative performance directly but indirectly via decreasing employee techno-work engagement and that employee-perceived digital technology complexity harms employee techno-work engagement and thus employee innovative performance via reduced usefulness perceptions and increasing levels of techno-strain perceptions, this study adds to scholars' understanding of how individuals react to the difficulties and negative aspects of digital technology usage and how this affects innovation, creativity, and performance, which is important for research on effectively working in digital settings (Tarafdar et al., 2019).

Moreover, this study contributes to research on the drivers of employees' innovative performance. It also furthers knowledge on the role of digital technologies and digital infrastructure in innovative processes and how these enable and constrain innovation (Nambisan et al., 2017, 2019). This was done by analyzing how employee-perceived digital technology usefulness and complexity affected employee innovation and by identifying employee techno-work engagement as an important proximal determinant of employee innovative performance. With this, I was also able to respond to Braukmann et al.'s (2018) call to examine the effects of digital technology use on individual employee performance. Additionally, I found employee-perceived digital technology complexity to evoke employee-perceived techno-strain and that employee-perceived techno-strain and employee-perceived usefulness indirectly affected employee innovative performance via employee techno-work engagement. The usability of the digital technologies at an employee's workplace (Ayyagari et al., 2011) thus seems to play an

important role in fostering innovative performance. Consequently, this study provides insights on how to design a digitalized work environment that encourages employees' innovative activities (see, e.g., Nöhammer & Stichlberger, 2019).

To my knowledge, this study is one of the first to apply and empirically test both paths of the job demands-resources model to the context of workplace digital technologies and their effect on employee performance.⁸ Thus, by theorizing and examining employee-perceived digital technology usefulness as a digital-technology-related job resource and employee-perceived digital technology complexity as a digital-technology-related job demand, this study contributes to the job demands-resources model literature. It is in line with Day et al. (2010), Kim and Christensen (2017), and J. R. Carlson et al. (2017), who suggested that the digital technologies at an employee's workplace might be job resources and demands. In doing so, I also add further empirical evidence to arguments and findings from previous studies on digital technologies as a double-edged sword (e.g., Diaz et al., 2012; Tarafdar et al., 2019).

4.6.2 Managerial Implications

The findings of this study may help managers and consultants who want to promote employees' innovative performance in their organizations. The results increase our understanding of how an organization's digital infrastructure and its characteristics influence employees' innovative performance. On the one hand, I found employee-perceived digital technology usefulness to indirectly foster innovative performance through employee techno-work engagement. On the other hand, I found a negative sequential indirect effect of employee-perceived digital technology complexity on employee innovative performance through employee-

⁸ Day et al. (2010) and Kim and Christensen (2017) used it as a framework in their conceptual papers. J. R. Carlson et al. (2017) applied the full model to empirically analyze the effect of digital technology usage on employee turnover intentions but did not investigate effects on employee performance.

perceived techno-strain and employee-perceived digital technology usefulness and employee techno-work engagement. Hence, I recommend that managers who strive to increase the innovative performance of their workforce promote employee-perceived digital technology usefulness and reduce employee-perceived digital technology complexity.

To attain high usefulness perceptions, organizations are well-advised to design and customize their digital technologies to support their users' tasks and produce effective and job-relevant results that can be directly observed and attributed to the respective digital technology (Venkatesh & Davis, 2000). Organizations may also offer employees the opportunity to participate in the technologies' development and implementation activities such as system evaluation and customization, prototype testing, and business process change initiatives (Venkatesh & Bala, 2008). Additionally, management could empirically demonstrate to their employees that the digital technologies at their workplace are more effective than those commonly used by other departments or competitors (Venkatesh & Davis, 2000). Moreover, as social influences are drivers of individuals' perceptions of usefulness (Venkatesh & Bala, 2008), managers should clearly communicate and emphasize the positive consequences for employee performance of using their organization's digital-technology infrastructure.

To decrease employee-perceived complexity, organizations could offer training and thus enhance their employees' digital-technology-related self-efficacy and reduce their anxieties related to the use of those technologies (Ong & Lai, 2006; Venkatesh, 2000). Game-based training might be particularly useful in such contexts since research has shown a positive relationship between a more enjoyable experience during training and perceiving a digital technology to be less complex (Venkatesh, 1999). Consequently, organizations should design their digital technologies such that using them is enjoyable (Venkatesh, 2000; Venkatesh & Bala, 2008). Organizations could also provide helpdesks and internal and external experts or facilitate

and promote the sharing of technical knowledge to help users overcome problems and hurdles when using digital technologies (Tarafdar et al., 2015, Venkatesh, 2000; Venkatesh & Bala, 2008).

4.6.3 Limitations and Implications for Future Research

As with every study, this study has limitations that offer avenues for future research. First, all of my data was self-reported and obtained from the same source, which could produce common method bias (Podsakoff et al., 2003). To reduce this problem, I used a three-phase study design that measured independent and mediator variables as well as the dependent variable at three different points in time (Podsakoff et al., 2003). I also performed post hoc confirmatory factor analyses testing one-factors models (Korsgaard & Roberson, 1995; Mossholder et al., 1998; Podsakoff et al., 2003) and models with a marker variable (Lindell & Whitney, 2001) to identify whether data is seriously affected by common method bias. Results indicated that common method bias might not be a large threat to my data. Nevertheless, future research might account for this and could validate my findings using field-experimental or quasi-experimental manipulations of the usefulness and complexity of the digital technologies that employees use. Furthermore, future research might also use physiological instruments to measure techno-strain (e.g., heart rate, oxygen consumption, or myoelectric signals; Hernandez et al., 2002) or techno-work engagement (e.g., galvanic skin response, electroencephalogram, and facio-muscular emotional recognition; Moreno et al., 2020).

Second, the sample size did not reach the common recommendations for a minimum sample size of 180 (for small mediation models; Wolf et al., 2013) or 200 (e.g., Boomsma & Hoogland, 2001; B. O. Muthén & Asparouhov, 2015) for performing structural equation modeling with multiple manifest indicators. I, therefore, generated latent variables by using the

composite scale of each first-order construct as the single indicator (Cole & Preacher, 2014). To avoid biased results, I corrected for measurement unreliability by applying the approach suggested by Schumacker and Lomax (2010). However, as “error reduction is better than error correction” (Cole & Preacher, 2014, p. 311), future studies could compile a larger sample and test my hypotheses using the full-measurement model with all respective indicators.

Third, this study examined the effects of the perceived usefulness and complexity of the digital technologies at the employees’ workplace in general rather than analyzing the effects of specific digital technologies. However, employees use different digital technologies, which should differ in their usefulness and complexity. Furthermore, as memory erodes over time (D. S. Evans & Leighton, 1995), employees might have based their answers primarily on the digital technologies used recently or most often. Moreover, it would also be interesting to know which digital technologies in particular foster employee innovative performance. Thus, future research could analyze the relationships of employee-perceived digital technology usefulness and complexity with employee innovative performance via employee techno-work engagement and employee-perceived techno-strain for various specific digital technologies.

Fourth, employees’ perceptions of the usefulness and the complexity of the digital technologies at their workplace should also depend on the respective tasks they have to accomplish (B. Wu & Chen, 2017). However, tasks may vary between days. Previous studies indicated that techno-work engagement and innovative performance (Orth & Volmer, 2017), as well as techno-strain (Nöhammer & Stichlberger, 2019), could be subject to daily changes. Consequently, future studies should account for this and examine how day-specific perceptions of digital technology usefulness and complexity influence daily innovative performance.

Fifth, personal resources were not considered. According to the job demands-resources model, *personal resources*, which refer to “aspects of the self that are generally linked to

resiliency” (Hobfoll et al., 2003, p. 632), play a similar role as job resources (Bakker & Demerouti, 2017). Typical examples of personal resources are self-efficacy, organization-based self-esteem, and optimism (see, e.g., Xanthopoulou et al., 2009). Thus, personal resources should be directly and positively related to work engagement, buffer the effects of job demands on strain, and be perceived as particularly motivating when job demands are high (Bakker & Demerouti, 2017). Previous research indicates that *digital-technology-related self-efficacy*, the judgment of an employee’s capability to use digital technologies (Compeau & Higgins, 1995), might be a personal resource that plays a role in the domain of digital-technology-related job resources and demands (e.g., Day et al., 2010). Although it has already been found to be a determinant of techno-work engagement (Mäkineniemi et al., 2019, 2020), future research could examine whether employees’ digital-technology-related self-efficacy moderates the relationship between employee-perceived digital technology usefulness and employee techno-work engagement on the one hand and between employee-perceived digital technology complexity and employee-perceived techno-strain on the other hand.

4.7 Conclusion

This study investigated how employee-perceived digital technology usefulness and employee-perceived digital technology complexity relate to employee innovative performance. In doing so, it contributes to our understanding of how the characteristics of an organizations’ digital-technology infrastructure affect employees’ innovative activities. Drawing on the job demands-resources model, I found employee-perceived digital technology usefulness to have a positive indirect effect on employee innovative performance through employee techno-work engagement. Moreover, I did not find employee-perceived digital technology complexity to have a statistically significant relationship with employee innovative performance through employee-

perceived techno-strain. However, employee-perceived digital technology complexity still had adverse consequences because it negatively affected employee techno-work engagement and consequently employee innovative performance through either employee-perceived digital technology usefulness or employee-perceived techno-strain. Therefore, digital technology characteristics and thus digital-technology-related job resources and job demands play an important role in employees' innovative performance. On the one hand, this is because digital-technology-related job resources seem to foster employee motivation when working with those technologies and thus create a motivational impetus that stimulates innovative performance. On the other hand, digital-technology-related job demands can pose a threat to employee innovative performance because they have the potential to reduce the motivational impetus that spurs innovative performance.

5. Friend or Foe? Digital Technologies and Daily Employee Innovative Behavior

5.1 Abstract

Based on affective events theory and conservation of resources theory, this chapter examines how perceived daily techno-support and perceived daily techno-stressors are related to daily employee innovative behavior. Findings here are based on a diary study with two daily surveys over the course of ten workdays with 1,727 data points nested in 94 employees working full-time. These showed a statistically significant and positive indirect effect of perceived daily support for communication and collaboration and perceived daily ease of effort on daily employee innovative behavior through daily high-activated positive mood. Furthermore, perceived daily information overload and perceived daily communication overload had a statistically significant and negative indirect effect on daily employee innovative behavior through daily high-activated positive mood and, contrary to our expectations, a statistically significant and positive indirect effect through daily high-activated negative mood. The results provide support for perceived daily techno-support and daily techno-stressors as affective work events that cause affective reactions in the form of daily high-activated positive and negative moods. These, in turn, trigger affect-driven behavior such as daily employee innovative behavior.

Keywords: activated mood; daily techno-support; daily techno-stressors; daily employee innovative behavior; diary study

5.2 Introduction

As organizations need to achieve competitive advantages to secure their long-term survival in today's rapidly changing business environment and highly competitive global marketplace (Pieterse et al., 2010), employee innovative behavior has become increasingly important (Anderson et al., 2014). Employee innovative behavior refers to employees' exploration, generation, championing, and implementation of innovative ideas (de Jong & den Hartog, 2010; Janssen, 2000; Scott & Bruce, 1994). It allows organizations to continuously develop new products, services, and work processes (de Jong & den Hartog, 2010) and contributes to organizational effectiveness (Janssen, 2000, 2003).

Given its importance, cross-sectional between-person studies examining the determinants of employee innovative behavior have burgeoned in organizational behavior research (Orth & Volmer, 2017). Previous studies have found that employee innovative behavior fluctuates between days (see, e.g., Madrid et al., 2014; Williamson et al., 2019) because innovative processes entail collaborating with others (Kanter, 1988; Madrid et al., 2014) and depend on everyday transactions in the work environment (Amabile, 1988; Scott & Bruce, 1994; West, 2002). Thus, employee innovative behavior and its determinants particularly demand to be analyzed within individuals (Orth & Volmer, 2017). Consequently, scholars need to go beyond exploring employee innovative behavior from a static between-person perspective and apply study designs that account for individual and daily variation (Williamson et al., 2019). However, research that uses such approaches and examines the antecedents of employees' daily innovative behavior remains scarce (Orth & Volmer, 2017).

Digitalization and digital technologies are theorized to be drivers of innovative activities (see, e.g., Nambisan et al., 2017; Yoo et al., 2012). Digital technologies are defined as “products

or services that are either embodied in information and communication technologies or enabled by them” (Lyytinen et al., 2016, p. 49). However, research indicates that, in relation to their effect on daily employee innovative behavior, digital technologies may be a double-edged sword (e.g., Chandra et al., 2019; Diaz et al., 2012; Sonnentag et al., 2018). On the one hand, they can support employees’ innovative behaviors by helping them collaborate and communicate with others, retrieve information, and develop or explore new ideas (Day et al., 2010; Diaz et al., 2012; Sun & Teng, 2017). On the other hand, digital technologies can lead to higher information and communication inflows that exceed an individual’s limited processing capacities (Karr-Wisniewsky & Lu, 2010; Schultze & Vandenbosch, 1998). This, in turn, causes techno-stress, which can negatively affect employees’ innovative behaviors (de Clercq et al., 2016).

According to affective events theory (Weiss & Cropanzano, 1996), these daily digital-technology-related work events, whether positive or negative, cause affective reactions such as moods. *Moods* reflect the way employees temporarily feel when working (Bindl & Parker, 2010). To explain the different impacts on employee moods of these positive and negative digital-technology-related work events, we use conservation of resources theory, which is a motivation and stress theory (Hobfoll, 1989; Hobfoll et al., 2018) and thus particularly suited for this. Moods are experienced in the short run and fluctuate over time (Bindl & Parker, 2010; George, 1991). Mood has been found to be an antecedent of employee innovative behavior in between-person studies (see, e.g., Montani et al., 2018) and to predict weekly (e.g., Madrid et al., 2014) or daily employee innovative behavior (see, e.g., Williamson et al., 2019). Thus, drawing on affective events theory and proposing mood as a mediator, this chapter analyzes how *perceived daily techno-support* (i.e., perceived daily support for communication and collaboration and perceived daily ease of effort of information retrieval) and *perceived daily techno-stressors* (i.e., perceived

daily information overload and perceived daily communication overload) relate to daily employee innovative behavior.

Our study provides several contributions. Following Orth and Volmer's (2017) call, we examine employee innovative behavior within individuals. Doing so allows us to explore why the innovative performance of the same employee differs between days (Breevaart & Zacher, 2019). Moreover, we contribute to explaining the determinants of an employee's daily inclination to innovate, which has mostly been neglected in research (Orth & Volmer, 2017). With this, we provide insights into how to foster employee innovative behavior in organizations. We also provide guidance for managers on how to promote such behavior on specific days when it might be particularly important to be innovative (e.g., in a specific phase of a project) (Breevaart & Zacher, 2019).

We also answer Nambisan et al.'s (2017) call to investigate the role of digital technologies in innovative processes. There is a growing body of literature theorizing on how digital technologies might enable or hinder innovative activities and outcomes (e.g., Kleinschmidt et al., 2016; Nambisan et al., 2017, 2019). However, there is little empirical research in this area – most existing research is conceptual – and our study contributes to filling this gap.

This is arguably the first study that theorizes and empirically tests perceived daily techno-support and perceived daily techno-stressors as antecedents of daily employee innovative behavior. We not only add to the literature on employee innovative behavior but also to research on digital technologies and digital innovation. In doing so, we also address rising calls to more closely examine the double-edged nature of digital technology usage and its effect on individual performance (Braukmann et al., 2018).

5.3 Theory and Hypotheses

5.3.1 Daily Techno-Support and Techno-Stressors, Daily High-Activated Moods, and Daily Employee Innovative Behavior – An Affective Events Theory Perspective

The focus of *affective events theory* is on describing the structure, causes, and consequences of affective experiences at work (Weiss & Cropanzano, 1996). The theory postulates that individuals' affective responses to work events largely determine their attitudes and subsequent behaviors (D. S. Carlson et al., 2011). These *affective work events* can be defined as things happening to people in work settings to which they react emotionally (Weiss & Cropanzano, 1996). Previous qualitative research by Braukmann et al. (2018) indicates that employees may, on a daily basis, have to deal with positive and negative digital-technology-related work events in the form of support for communication and collaboration and an effortless retrieval of information and feedback (positive) and information and communication overload (negative). As it is a fundamental assumption of the theory that affect levels fluctuate over time due to affectively relevant work events (Weiss & Cropanzano, 1996), we draw on affective events theory to analyze the effects of perceived daily techno-support and perceived daily techno-stressors on daily employee innovative behavior.

In the first stage, affective events theory links work events and affective reactions (Weiss & Cropanzano, 1996). These affective responses refer to employees' moods and emotions (D. S. Carlson et al., 2011). When confronted with work events, employees often experience both positive and negative moods (George & Zhou, 2007), which can be present at the same time (Bledow et al., 2013). *Positive mood* describes the extent to which a person feels enthusiastic, active, and alert and can be defined as a state of high energy, full concentration, and pleasurable engagement (George, 1995; Watson et al., 1988). *Negative mood* is a state of subjective distress

and unpleasurable engagement and is characterized by anger, contempt, disgust, guilt, fear, and nervousness (George, 1995; Watson et al., 1988). In the second stage, affective events theory postulates affective states and thus moods as the immediate determinants of *affect-driven behaviors*. These are behaviors triggered by an employee's direct affective reactions to a work event (Weiss & Cropanzano, 1996). Previous empirical research has identified employee innovative behavior as an affect-driven behavior (e.g., Madrid et al., 2014; Williamson et al., 2019).

Moods can differ in their activation (Russell, 1980). In contrast to low-activated mood, *high-activated mood* is characterized by a particularly high readiness for action or energy expenditure (Russell, 2003). High-activated moods increase the amount of effort put into a behavior (Brehm, 1999), while low-activated moods are associated with inactivity (Frijda, 1986; Parker et al., 2010). High-activated moods – in contrast to low-activated moods – create energy that provides the push for individuals to make active efforts to attain or avoid a particular outcome (Brehm, 1999; Cacioppo et al., 1999; Seo et al., 2010).

High-activated positive moods broaden an individual's cognitive flexibility and thought-action repertoires (Fredrickson, 1998). In turn, they ease the development of novel thoughts (Williamson et al., 2019) as well as thinking ahead and anticipating situations (Bindl et al., 2012). Employees with high-activated positive moods tend to invest more time and energy into activities (Seo et al., 2010) and tend to be more persistent (Bindl et al., 2012; George & Brief, 1996). This is important for generating, promoting, and realizing innovation that requires substantial efforts to, for example, deal with different viewpoints on ideas or people who want to prevent change (Janssen, 2003). High-activated positive moods provide the energizing potential (Bindl et al., 2012) that is necessary for the self-regulatory, goal-oriented, and persistent aspects of proactively creating, promoting, or implementing ideas (Fritz & Sonnentag, 2009). As such, they should

foster employee innovative behavior that requires challenging the status quo and pushing for the adoption of novel ideas (Madrid et al., 2014).

High-activated negative moods, by contrast, might trigger employees to actively withdraw from work to protect their well-being (Carver & White, 1994). This can make them withhold ideas for changing inefficient work policies or for developing new products or services (Madrid et al., 2015). High-activated negative moods narrow individuals' thought-action repertoires and their cognitive flexibility (Fredrickson, 1998). This affects the notification and recombination of ideas and reduces an employee's range of novel solutions for the generation, exploration, championing, and implementation of innovative ideas (de Jong & den Hartog, 2010; Janssen, 2000; Scott & Bruce, 1994; Williamson et al., 2019). Employees with high-activated negative moods also tend to stronger sense the risks associated with innovative behavior that challenges the status quo (Madrid et al., 2015). Thus, we suggest that daily high-activated positive moods should be positively related, and daily high-activated negative moods should be negatively related to daily innovative behavior.

In sum, based on affective events theory (Weiss & Cropanzano, 1996), we propose that daily techno-support (as positive digital-technology-related work events) and daily techno-stressors (as negative digital-technology-related work events) indirectly affect daily employee innovative behavior (as an affect-driven behavior) via daily high-activated positive and daily high-activated negative mood (as affective reactions), respectively. In the following, we further explore the specific nature of these indirect relationships by additionally integrating conservation of resources theory (Hobfoll, 1989, 2001). This perspective is introduced to further explore the relationships between daily techno-support and daily techno-stressors and the mediators, daily high-activated positive mood and daily high-activated negative mood.

5.3.2 Daily High-Activated Moods as Mediators Between Perceived Daily Techno-Support and Daily Employee Innovative Behavior

Recent research by Braukmann et al. (2018) hinted at daily support for communication and collaboration and ease of effort of information and feedback retrieval to be important digital-technology-related affective work events. *Perceived daily support for communication and collaboration* can be defined as the extent to which employees perceive that digital technologies have supported communicating and collaborating with others on the respective day (Sun & Teng, 2017). *Perceived daily ease of effort* is the extent to which employees perceive that digital technologies have enabled the effortless retrieval of information and feedback on the day in question (Kankanhalli et al., 2015).

According to conservation of resources theory, individuals have two fundamental goals that shape their actions and feelings: avoiding resource losses and accumulating new resources (Halbesleben et al., 2014; Hobfoll, 1989, 2001). It is individuals' basic motivation to protect and expand their resource pool (Halbesleben et al., 2014; Hobfoll, 1989, 2001; Ng & Feldman, 2012). Being confronted with positive work events leading to resource savings or gains that enable employees to reach that goal should result in high-activated positive moods. This is supported by the results of Bennett et al.'s (2018) meta-analysis, which found savings and gains of energy resources to be positively related to being in a state of high-activated positive mood. Moreover, as individuals are fundamentally motivated to protect their current resource pool and fear resource losses (Halbesleben et al., 2014; Hobfoll, 2001), experiencing or being threatened with resource loss has negative psychological consequences (Hobfoll, 1989) such as high-activated negative moods. However, with more resources at their disposal, individuals are shielded against the negative consequences of resource losses (Halbesleben et al., 2014; Hobfoll, 2001). Hence,

people being confronted with resource savings or gains should be less likely to be in high-activated negative mood states.

Digital technologies support effective and efficient communication with actors inside and outside the organization (Day et al., 2010), help employees coordinate their work with others (Doll & Deng, 2001), and ease the distribution and sharing of experiences and information (Bhatt et al., 2005). Consequently, techno-support allows employees to better communicate and to better work together and thus eases the interaction and integration with others (Sun & Teng, 2017). By supporting collaboration and communication and the effortless retrieval of information and feedback, digital technologies also allow the easy receipt of help and access to information and feedback in case of problems and thus facilitate and accelerate problem-solving (Day et al., 2010; Morgan et al., 2000). With this, techno-support enables employees to work more efficiently (see, e.g., von Briel et al., 2018). Consequently, as techno-support facilitates savings of time and energy resources that can be used to acquire other resources and thus satisfies both central motivations (i.e., protecting and enlarging an individual's resource pool), it should evoke positive moods high in activation (Ouweneel et al., 2012). Having positive consequences for employees' resource pools and protecting them from resources losses, daily techno-support should additionally reduce daily high-activated negative moods. Therefore, by triggering high-activated positive mood and reducing high-activated negative mood, daily techno-support should indirectly affect daily employee innovative behavior. Thus, based on affective events theory (Weiss & Cropanzano, 1996) and conservation of resources theory (Hobfoll, 1989, 2001), we propose:

Hypothesis 1: Daily high-activated positive mood mediates the relationship between a) perceived daily support for communication and collaboration and b) perceived daily ease of effort on the one hand and daily employee innovative behavior on the other hand such that the indirect effects are positive.

Hypothesis 2: Daily high-activated negative mood mediates the relationship between a) perceived daily support for communication and collaboration and b) perceived daily ease of effort on the one hand and daily employee innovative behavior on the other hand such that the indirect effects are positive.

5.3.3 Daily High-Activated Moods as Mediators Between Perceived Daily Techno-Stressors and Daily Employee Innovative Behavior

Results from Braukmann et al. (2018) indicated that information overload and communication overload might be important negative digital-technology-related work events that employees have to deal with on a daily basis. *Perceived daily information overload* can be defined as a state when individuals perceive that the volume and speed of incoming stimuli they have to cope with on a day (i.e., information load) exceed their processing capacities (Hiltz & Turoff, 1985; Schultze & Vandenbosch, 1998). *Perceived daily communication overload* refers to a state when individuals perceive the communication demands from digital technologies (e.g., incoming e-mails and instant messages) they have to face on a particular day to be beyond their processing capacities (Cho et al., 2011).

According to conservation of resources theory, the goal of individuals is to protect their resource pool, and they fear resource losses (Halbesleben et al., 2014; Hobfoll, 1989, 2001). Being confronted with events that potentially or actually lead to resource losses should foster high-activated negative moods and reduce high-activated positive moods. Feelings of being overloaded are associated with such a resource loss, namely a perceived loss of control over the situation (Bawden & Robinson, 2009).

Furthermore, conservation of resources theory argues that when individuals are confronted with situations that cause resource losses, they have to offset those by investing

resources (Hobfoll, 1989, 2001), which also decreases their resource pool. The use of digital technologies requires employees to simultaneously handle incoming information from internal and external sources (Ragu-Nathan et al., 2008). The amount of available information has increased, but the workload has not decreased, which limits the time employees have to process information and to filter what is relevant (Day et al., 2012; Johansson-Hiden et al., 2003; Tarafdar et al., 2010). The increased inflow of information also pressures employees into attending to information as soon as it arrives, which makes sustained mental attention difficult (Tarafdar et al., 2011). Similarly, constant inflows of digital-technology-based communication (e.g., e-mails, instant messages) cause interruptions (Karr-Wisniewski & Lu, 2010). For example, when receiving an e-mail, employees tend not to delay answering to a time that is more convenient but to react within six seconds (Jackson et al., 2003). However, repeated exposure to interruptions poses significant demands for employees' mental regulation and attention shifting; they must attend to multiple stimuli, need to schedule and prioritize interruptions and primary activities, and have to switch to the interruptions and back (Addas & Pinsonneault, 2018). Thus, when employees face information and communication overload, they have to invest energy and time resources to process the information, recover from interruptions, and think about and respond to incoming messages (Harris et al., 2015). This leads to a forced reduction of their resource pool. This should foster high-activated negative moods, given that individuals aim at protecting their resources and are threatened by depletion of their resource pool (Hobfoll, 1989, 2001). Additionally, research by Barley et al. (2011) indicates that information and communication overload could result in high-activated negative moods among employees because they evoke anxieties such as the fear of falling behind in one's work and the fear of missing important information.

As information and communication overload cause resource losses (Harris et al., 2015), which employees fear (Hobfoll, 2001), perceiving techno-stressors should also have a negative effect on their high-activated positive moods. This is supported by previous research, which has found negative relationships between techno-stress and positive moods (Brooks, 2015). Hence, by fostering high-activated negative mood and negatively affecting high-activated positive mood, perceiving daily techno-stressors should indirectly affect daily employee innovative behavior. Thus, based on affective events theory (Weiss & Cropanzano, 1996) and conservation of resources theory (Hobfoll, 1989, 2001), we propose:

Hypothesis 3: Daily high-activated negative mood mediates the relationship between a) perceived daily information overload and b) perceived daily communication overload on the one hand and daily employee innovative behavior on the other hand such that the indirect effects are negative.

Hypothesis 4: Daily high-activated positive mood mediates the relationship between a) perceived daily information overload and b) perceived daily communication overload on the one hand and daily employee innovative behavior on the other hand such that the indirect effects are negative.

5.4 Method

5.4.1 Sample

Participants in our study were employees working full-time in German organizations. With the help of a team of six student research assistants, we recruited potential participants matching our inclusion criteria via the research assistants' professional and social networks (for a similar procedure, see, e.g., Biron & van Veldhoven, 2016; Müller & Niessen, 2019). This was done to achieve a heterogeneous sample and to increase the generalizability of our findings (Demerouti & Rispens, 2014). We provided potential participants with information on the goal of

the project and guaranteed them confidential and voluntary participation. They were given the option to receive a short summary of the study's main results as an incentive. In total, 143 employees expressed interest in participating. Of those, 94 filled out the general questionnaire and met the inclusion criteria by answering both daily surveys for at least three consecutive workdays, which reflects a response rate of 65.73%. In sum, our analyses were based on 94 individuals providing a total of 1,727 data points. With this, we exceeded the minimum sample size of 83 participants or 835 data points recommended by Gabriel et al. (2019).

In our final sample, 46.81% of the respondents were women. The average participant was 38.77 years old ($SD = 12.85$; $MIN = 22$ years; $MAX = 62$ years), with 15.60 years of working experience ($SD = 12.94$; $MIN = 1$ year; $MAX = 44$ years), and a job tenure of 9.53 years ($SD = 10.25$; $MIN < 6$ months; $MAX = 44$ years). Additionally, 51.06% held a university (or comparable) degree, and 5.32% had a Ph.D. Respondents were employed in various industries. Of these, 23.40% held a leadership position in their respective organization and 12.77% were blue-collar workers. Regarding hierarchy level, 54.26% held operational positions, 26.60% had lower-management positions, 11.70% were in middle management, and 7.45% in upper-management positions.

5.4.2 Procedure

To empirically test our hypotheses, we conducted a quantitative diary study. All data collection was carried out via online questionnaires in two distinct phases. In Phase 1, participants had to answer a general questionnaire that contained questions on socio-demographics and stable control variables. In Phase 2, which started approximately two weeks after the initial general survey, we asked participants to respond to two daily online surveys for a period of ten working days (Monday to Friday). The first daily survey had to be answered at the beginning of the lunch

break, and the second had to be answered at the end of the workday. This was done because previous research by Barley et al. (2011) found that work communication (and thus incoming information and interruptions) has two peaks: in the morning and in the afternoon. We considered our participants' specific worktime arrangements and sent invitations and reminders of the daily surveys to assure timely receipt. All day-specific variables were assessed in both daily surveys.

Following Binnewies and Wörnlein's (2011) and Niessen et al.'s (2012) suggestions, we timestamped all daily assessments, carefully checked the data before analyzing it, and deleted questionnaires that were answered at the wrong time of day (e.g., when the lunchtime questionnaire was filled out in the evening) or day of the week (e.g., when a questionnaire that had to be answered at the end of the workday on Monday was answered on Tuesday at lunchtime). Furthermore, to maximize statistical power, we only included respondents in our final sample if they had completed at least the noon and afternoon survey on three consecutive workdays (see, e.g., Bormann, 2017; Trougakos et al., 2014; Zacher et al., 2015).

5.4.3 Measures

To measure our variables, we selected suitable and reliable scales and items from previously validated instruments. We followed the suggestions of Brislin (1970) and S. P. Douglas and Craig (2007) to use a bilingual committee approach in combination with pretest procedures to translate those scales into German. Participants had to rate the extent to which they perceived the respective techno-support and techno-stressor variables. They also rated the extent to which they felt being in a state of high-activated positive and negative mood and to which they behaved innovatively. These ratings were assessed on a five-point Likert-type scale (1 = *not at all* to 5 = *extremely*). In the daily surveys, respondents were asked to evaluate the "past hours (since the beginning of the workday)" in the lunchtime surveys and the "past hours (since the questionnaire at lunchtime)" in the surveys

to be answered at the end of the workday. Scales that were used to assess day-specific variables were slightly adapted to refer to the “past hours.” Moreover, techno-support and techno-stressor variables were adapted so that they measured the extent to which participants perceived the relevant digital-technology-related affective work event. Adapting items originally developed to assess between-person phenomena is typical in diary study designs (Ohly et al., 2010). Following the recommendations by Geldhof et al. (2014), we estimated the Cronbach's alpha of the variables from the daily surveys at two levels: within-person and between-persons.

To measure perceived daily support for communication and collaboration, we adapted the four-item scale of Sun and Teng (2017) to refer to the digital technologies at the respondent's workplace instead of the use of corporate information systems as in the original version. A sample item (here for the survey at lunchtime) is “During the past hours (since the beginning of your workday), to what extent has using the digital technologies at your workplace supported you in cooperating and collaborating more closely with your colleagues?” The within-person alpha was .86, and the between-person alpha was .98.

Perceived daily ease of effort was assessed by drawing on a three-item scale from Kankanhalli et al. (2015). Originally measuring the ease of effort of designing service applications, the scale was adapted to reflect the daily ease of effort of collecting information and feedback. A sample item (here for the survey at lunchtime) is “During the past hours (since the beginning of your workday), to what extent have the digital technologies at your workplace helped you save a lot of effort for collecting information and feedback?” The within-person alpha was .73, and the between-person alpha was .86.

We measured perceived daily information overload by using the four items that directly addressed employees' information load from the six-item scale of Schultze and Vandenberg (1998). Using shortened scales is typical in diary study designs to keep the response burden

reasonable and to ensure that participants regularly respond (Fisher & To, 2012). The scale was adapted to refer to the digital technologies at the respondent's workplace instead of the specific software "Notes." A sample item (here for the survey at the end of the workday) is "During the past hours (since the questionnaire at lunchtime), to what extent has using the digital technologies at your workplace increased the amount of unsolicited information you received?" The within-person alpha was .83, and the between-person alpha was .98.

To assess perceived daily communication overload, we used three items from the scales of Karr-Wisniewsky and Lu (2010) and Galluch et al. (2015). The items were adapted compared to the original version so that they specifically measured the interruptions and distractions caused by incoming digital messages. A sample item (here for the survey at the end of the workday) is "During the past hours (since the questionnaire at lunchtime), to what extent have you experienced distractions caused by incoming digital messages (e.g., e-mails, instant messaging)?" The within-person alpha was .76, and the between-person level alpha was .87.

Regarding mediators, we measured daily high-activated moods with four items each by drawing on the multi-affect indicator (Warr et al., 2014). In both daily surveys, respondents were asked to indicate the extent to which they felt enthusiastic, excited, inspired, and joyful during the past hours (since the beginning of the workday or since the last questionnaire, respectively) for assessing daily high-activated positive mood and the extent to which they felt anxious, nervous, tense, and worried for measuring daily high-activated negative mood. The within-person alpha was .68 for daily high-activated positive mood and .65 for daily high-activated negative mood, which is still acceptable (see, e.g., Minbashian et al., 2018; Park et al., 2020). The between-person alpha was .94 and .93, respectively.

The dependent variable, daily employee innovative behavior, was measured by Williamson et al.'s (2019) four-item scale, a short version of the scale used by de Jong and den Hartog (2010).

The short scale was specifically designed to be used in diary studies and reflects each of de Jong and den Hartog's (2010) four dimensions of employee innovative behavior: idea generation, idea exploration, idea championing, and idea implementation (Williamson et al., 2019). Consequently, we asked participants to rate the extent to which they generated original solutions for problems (idea generation), wondered how things could be improved (idea exploration), attempted to convince people to support an innovative idea (idea championing), and put effort into developing something new (idea implementation) during the past hours (since the beginning of the workday or since the last questionnaire, respectively). The within-person alpha was .84, and the between-person alpha was .98.

We also included several control variables on the between-person level (Level 2) and the within-person level (Level 1). For Level 1, we controlled for the effects of a work event aimed at improving innovative activities that might have happened during the specific part of the day. To assess this, we asked participants whether they took part in a workshop, meeting, or similar event aimed at recognizing new business opportunities, or developing, promoting, and/or realizing ideas during the past hours (since the beginning of the workday or since the last questionnaire) (0 = *no*, 1 = *yes*). To avoid biased results, we also controlled for data collection daytime (0 = *lunchtime*, 1 = *end of workday*). Furthermore, we considered age, sex, innovativeness as a job requirement, and positive and negative trait affect as Level 2 controls. Age (measured as a continuous variable), sex (0 = *men*, 1 = *women*), and positive and negative trait affect have been identified as important control variables by previous studies analyzing mood and employee innovative behavior (e.g., Madrid et al., 2014; Williamson et al., 2019). Positive trait affect ($\alpha = .73$) and negative trait affect ($\alpha = .74$) were assessed by drawing on Madrid et al.'s (2014) short version of the positive and negative affect schedule (Watson et al., 1988). Participants had to indicate the extent to which they, in general, felt five positive (enthusiastic, excited, strong, interested, determined) and five negative

(irritable, jittery, hostile, upset, nervous) emotions on a five-point Likert-type scale (1 = *not at all* to 5 = *extremely*). Additionally, we included innovativeness as a job requirement ($\alpha = .75$) as a control variable because it has been found to influence employee innovative behavior (e.g., Gilson & Shalley, 2004; Yuan & Woodman, 2010). It was measured with a five-item scale from Yuan and Woodman (2010). A sample item is “Introducing new ideas into the organization is part of my job.” The items had to be rated on a five-point Likert-type scale (1 = *does not apply at all* to 5 = *fully applies*).

5.4.4 Data Analysis

Having data from the between-person level (Level 2) and the within-person level (Level 1) with daily measurements being nested within persons, we applied multilevel techniques to analyze the data using MPlus (Version 8.4). We tested our model by employing a multilevel structural equation model (Preacher et al., 2010). We constructed a (1,1,1,1)-(1,1)-1 mediation model because all focal variables were measured at the within-person level (Level 1). The first part represents the four independent variables, the second part the two mediators, and the last one refers to the dependent variable. By partitioning and estimating between- and within-person associations, multilevel structural equation modeling allows us to account for the non-independence of multiple responses from the same individual (Williamson et al., 2019). Multilevel structural equation modeling does not require centering (Preacher et al., 2010). Some normality assumptions such as homoscedasticity might lead to problems for multilevel modeling (Finney & DiStefano, 2006). We, therefore, applied maximum likelihood estimation with robust standard errors, which is robust to non-normality issues (Muthén & Muthén, 2017).

5.5 Results

5.5.1 Statistics, Measurement Models, and Test for Common Method Bias

Table 10 shows means, standard deviations, and both within-person level and between-person level correlations among model and control variables. We averaged the within-person variables across the twenty data-collection occasions to calculate the between-level correlations (see, e.g., Binnewies & Wörnlein, 2011).

In a first step, to test for the appropriateness of a multilevel modeling approach, the between-level variance for our focal variables was computed. The intraclass correlation coefficient was .50 for perceived daily support for communication and collaboration, .44 for perceived daily ease of effort, .48 for perceived daily information overload, .39 for perceived daily communication overload, .63 for high-activated positive mood, .56 for high-activated negative mood, and .41 for daily employee innovative behavior. Thus, large amounts of variance remained to be explained by within-level fluctuations, which supported the appropriateness of a multilevel analysis.

Table 10*Descriptive Statistics and Correlations of Study 4 Variables*

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
<i>Level 1 (within-persons)</i>															
1. Perceived daily support for communication and collaboration	2.94	1.00	1	.62**	.20**	.18**	.31**	.07**	.33**	.16**	-.06*				
2. Perceived daily ease of effort	3.11	0.98	.76**	1	.22**	.23**	.24**	.08**	.30**	.09**	-.05*				
3. Perceived daily information overload	1.97	0.86	.19	.22*	1	.73**	-.03	.34**	.19**	-.05	-.03				
4. Perceived daily communication overload	2.22	0.92	.15	.19	.89**	1	-.07**	.35**	.14**	-.04	-.05*				
5. Daily high-activated positive mood	2.63	0.77	.46**	.36**	.05	-.04	1	-.22**	.41**	.16**	-.02				
6. Daily high-activated negative mood	1.58	0.65	.06	.11	.42**	.45**	-.16	1	.07**	-.01	-.04				
7. Daily employee innovative behavior	2.11	0.97	.38**	.40**	.26*	.20	.59**	.07	1	.39**	-.03				
8. Work event aimed at improving innovative activities	0.17	0.38	.23*	.19	-.08	-.12	.23*	-.07	.50**	1	-.06*				
9. Data collection daytime	0.50	0.50	-	-	-	-	-	-	-	-	-	-	-	-	-
<i>Level 2 (between-persons)</i>															
10. Age	38.77	12.79	-.16	-.16	-.05	-.07	-.10	-.09	-.00	-.06	-	1			
11. Sex	0.47	0.50	-.00	.09	-.08	-.02	.05	-.07	-.09	-.10	-	.03	1		
12. Positive trait affect	3.28	0.62	.31**	.29**	.18	.11	.33**	-.00	.15	.02	-	.06	.15	1	
13. Negative trait affect	1.63	0.54	-.16	-.15	.25*	.20	-.21*	.38**	.09	-.08	-	-.01	-.15	-.18	1
14. Innovativeness as a job requirement	3.11	0.83	.22*	.26*	.05	.04	.31**	-.04	.44**	.40**	-	-.01	-.08	.32**	.09

Note. Correlations below the diagonal are between-person level correlations ($N = 94$). Correlations above the diagonal are within-person level correlations ($N = 1,727$). Sex is coded 0 = *men* and 1 = *women*. Data collection daytime is coded 0 = *lunchtime* and 1 = *end of workday*. Between-person level correlations of data collection daytime could not be computed because it is constant on that level.

* $p < .05$, ** $p < .01$

Furthermore, a multilevel confirmatory factor analysis was conducted to test the fit of the hypothesized model variables to the data. Results showed that our model fitted the data acceptably ($\chi^2 = 2232.95$, $df = 1012$, $p < .01$, CFI = .94, TLI = .93, RMSEA = .03, SRMR_{within} = .04, SRMR_{between} = .08). In addition, we compared our measurement model to an alternative model solution with measures of the techno-support and techno-stressors variables both loading on one factor ($\chi^2 = 4455.60$, $df = 1040$, $p < .01$, CFI = .82, TLI = .80, RMSEA = .04, SRMR_{within} = .06, SRMR_{between} = .08, Satorra-Bentler scaled chi-square difference⁹ (Δ S-B χ^2) = 1613.04, $p < .01$), which had a worse fit. This strengthened our confidence in the assumed measurement structure.

As our data was based on self-reports by the same person, there is a risk that the results from our analyses might be confounded by common method variance. To examine whether common method variance might be an issue, we tested whether a single-factor model fitted the data as well as our assumed measurement model (Korsgaard & Roberson, 1995; Mossholder et al., 1998; Podsakoff et al., 2003). However, the single-factor model provided a worse fit to the data ($\chi^2 = 14915.82$, $df = 1078$, $p < .01$, CFI = .27, TLI = .23, RMSEA = .08, SRMR_{within} = .16, SRMR_{between} = .26, Δ S-B $\chi^2 = 20132.44$, $p < .01$). Thus, although this does not necessarily rule out the potential for common method variance in our data, it indicates that it is unlikely that common method variance substantially affected our data (for multilevel studies that used similar procedures, see Madrid et al., 2014; Williamson et al., 2019).

⁹ As it is recommended when using maximum likelihood estimation with robust standard errors, the Satorra-Bentler scaled chi-square difference test was applied to compare models (Satorra & Bentler, 2001). It incorporates a scaling correction for the chi square statistic when violations of distributional assumptions occur (B. M. Byrne, 2010).

5.5.2 Hypothesis Testing

Unstandardized coefficients are reported in the following sections. Regarding Level 1 control variables, results revealed that data being collected at the end of the workday was statistically significantly and negatively related to daily high-activated positive mood (*within-person level path coefficient (coeff.)* = -0.04, $p < .01$), not statistically significantly related to daily high-activated negative mood, and statistically marginally significantly and negatively related to daily employee innovative behavior (*coeff.* = -0.07, $p = .06$). Moreover, having attended a work event aimed at improving innovative activities was statistically significantly and positively related to daily employee innovative behavior (*coeff.* = 0.59, $p < .01$). Regarding Level 2 controls, positive and negative trait affect were not statistically significantly related to high-activated positive mood. However, negative trait affect was statistically significantly and positively related to daily high-activated negative mood (*coeff.* = 0.27, $p < .01$), while positive trait affect was not. We found a statistically marginally significant negative relationship of positive trait affect (*coeff.* = -0.16, $p = .05$), a statistically significant positive relationship of negative trait affect (*coeff.* = 0.26, $p < .01$), and a statistically significant positive relationship of innovativeness as a job requirement with daily employee innovative behavior (*coeff.* = 0.19, $p < .01$). Age and sex were not statistically significantly related to daily high-activated positive mood, daily high-activated negative mood, and daily employee innovative behavior.

Table 11 displays the path and mediation results of our focal variables. As all of our hypotheses refer to the within-person level, results displayed in this section are based on within-person estimates. In line with Hypotheses 1a and 1b, we found a statistically significant and positive indirect effect of perceived daily support for communication and collaboration (*coeff.* = 0.02, $p = .02$) and perceived daily ease of effort (*coeff.* = 0.01, $p = .03$) on daily employee

innovative behavior through daily high-activated positive mood. The direct effects of perceived daily support for communication and collaboration ($coeff. = 0.06, p < .01$) and perceived daily ease of effort ($coeff. = 0.04, p = .02$) on daily high-activated positive mood were also statistically significant and positive. Furthermore, results showed a statistically significant and positive relationship between daily high-activated positive mood and daily employee innovative behavior ($coeff. = 0.31, p < .01$). Contrary to our expectations, we also found a statistically significant and positive relationship between daily high-activated negative mood and daily employee innovative behavior ($coeff. = 0.12, p < .01$).

However, the indirect effects of perceived daily support for communication and collaboration ($coeff. = 0.00, p = .23$) and perceived daily ease of effort ($coeff. = -0.00, p < .41$) on daily employee innovative behavior through daily high-activated negative mood were not statistically significant. Hence, Hypotheses 2a and 2b did not receive support. Additionally, the direct effects of perceived daily support for communication and collaboration ($coeff. = 0.03, p = .17$) and perceived daily ease of effort ($coeff. = -0.02, p = .37$) on daily high-activated negative mood were not statistically significant.

Furthermore, contrary to our expectations, the indirect effects of perceived daily information overload ($coeff. = 0.01, p = .04$) and perceived daily communication overload ($coeff. = 0.01, p = .01$) on daily employee innovative behavior through daily high-activated negative mood were statistically significant and positive. Therefore, Hypotheses 3a and 3b did not receive support. However, we found the direct effects of perceived daily information overload ($coeff. = 0.11, p < .01$) and perceived daily communication overload ($coeff. = 0.10, p < .01$) on daily high-activated negative mood to be positive.

Finally, results revealed the indirect effects of perceived daily information overload ($coeff. = -0.03, p = .01$) and perceived daily communication overload ($coeff. = -0.02, p < .01$) on

daily employee innovative behavior via daily high-activated positive mood to be statistically significant and negative providing support for Hypotheses 4a and 4b. Perceived daily information overload (*coeff.* = -0.08, $p < .01$) and perceived daily communication overload (*coeff.* = -0.07, $p < .01$) both had a statistically significant negative effect on daily high-activated positive mood.

Table 11*Multilevel Model Predicting Daily Employee Innovative Behavior: Within-Person Level Paths*

Path	Estimate	SE	p
<i>Direct paths</i>			
Perceived daily support for communication and collaboration → Daily high-activated positive mood	0.06	.02	< .01
Perceived daily ease of effort → Daily high-activated positive mood	0.04	.02	.02
Perceived daily information overload → Daily high-activated positive mood	-0.08	.03	< .01
Perceived daily communication overload → Daily high-activated positive mood	-0.07	.02	< .01
Perceived daily support for communication and collaboration → Daily high-activated negative mood	0.03	.02	.17
Perceived daily ease of effort → Daily high-activated negative mood	-0.02	.02	.37
Perceived daily information overload → Daily high-activated negative mood	0.11	.04	< .01
Perceived daily communication overload → Daily high-activated negative mood	0.10	.03	< .01
Daily high-activated positive mood → Daily employee innovative behavior	0.31	.05	< .01
Daily high-activated negative mood → Daily employee innovative behavior	0.12	.04	< .01
<i>Indirect paths</i>			
H1a: Perceived daily support for communication and collaboration → Daily high-activated positive mood → Daily employee innovative behavior	0.02	.01	.02
H1b: Perceived daily ease of effort → Daily high-activated positive mood → Daily employee innovative behavior	0.01	.01	.03
H2a: Perceived daily support for communication and collaboration → Daily high-activated negative mood → Daily employee innovative behavior	0.00	.00	.23
H2b: Perceived daily ease of effort → Daily high-activated negative mood → Daily employee innovative behavior	-0.00	.00	.41
H3a: Perceived daily information overload → Daily high-activated negative mood → Daily employee innovative behavior	0.01	.01	.04
H3b: Perceived daily communication overload → Daily high-activated negative mood → Daily employee innovative behavior	0.01	.00	.01
H4a: Perceived daily information overload → Daily high-activated positive mood → Daily employee innovative behavior	-0.03	.01	.01
H4b: Perceived daily communication overload → Daily high-activated positive mood → Daily employee innovative behavior	-0.02	.01	< .01

Note. $N_{within} = 1,727$; $N_{between} = 94$.

5.5.3 Supplementary Analyses

Employees often switch devices throughout the day (Oulasvirta & Sumari, 2007). Furthermore, work communication and thus incoming information and interruptions have peaks in the morning and in the afternoon (Barley et al., 2011). Therefore, perceptions of techno-support and techno-stressors and their effect on daily high-activated moods and daily employee innovative behavior should differ between the two halves of the workday. Thus, in our main analysis, we examined the relationships between perceived daily techno-support and techno-stressors and daily employee innovative behavior via daily high-activated moods with variables all measured at the same half of the day.

However, we performed two supplementary analyses to shed additional light on the indirect relationships between perceived daily support for communication and collaboration, perceived daily ease of effort, perceived daily information overload, and perceived daily communication overload on the one hand and daily employee innovative behavior on the other hand through daily high-activated moods.

First, we examined the relationships of techno-support and techno-stressors perceived during the first half of the workday (measured at lunchtime) and employee innovative behavior during the second half of the workday (measured at the end of the workday). We looked at how these are mediated by high-activated moods during the first half of the workday (also measured in the survey at lunchtime). This was done to test if the effects of perceiving techno-support and techno-stressors on high-activated moods during the first half of the workday are strong enough to influence innovative activities later in the day. We found the relationship between high-activated positive mood during the first half of the workday (measured at lunchtime) and perceived communication overload during the first half of the workday (measured at lunchtime)

(*coeff.* = -0.06, $p = .05^{10}$) to be statistically significant and negative. However, there were no statistically significant relationships between this mood and perceived support for communication and collaboration, ease of effort, or perceived daily information overload during the first half of the workday (measured at lunchtime). We still found the statistically significant positive relationships of perceived information overload (*coeff.* = 0.11, $p = .02$) and perceived communication overload (*coeff.* = 0.07, $p = .04$) during the first half of the workday (assessed at lunchtime) with high-activated negative mood during the first half of the workday (measured at lunchtime). However, high-activated positive mood and high-activated negative mood during the first half of the workday (measured at lunchtime) did not statistically significantly relate to employee innovative behavior during the second half of the workday (assessed at the end of the workday). Consequently, we also did not find any statistically significant indirect effects.

Second, we investigated the relationships of perceived support for communication and collaboration, perceived ease of effort, perceived information overload, and perceived communication overload during the first half of the workday (measured at lunchtime) on employee innovative behavior during the second half of the workday (measured at the end of the workday) through high-activated moods during the second half of the workday (also measured at the end of the workday). This was done to test if perceiving techno-support and techno-stress during the first half of the day affects high-activated moods and employee innovative behavior later in the day. Here, we only found statistically significant relationships of high-activated positive mood (*coeff.* = 0.25, $p < .01$) and high-activated negative mood (*coeff.* = 0.22, $p < .01$) during the second half of the workday (measured at the end of the workday) with employee innovative behavior during the second half of the workday (assessed at the end of the workday).

¹⁰ The p -value is .05 due to due to rounding to two decimal places, it is smaller than .05.

We did not find statistically significant relationships of perceived support for communication and collaboration, perceived ease of effort, perceived information overload, and perceived communication overload during the first half of the workday (measured at lunchtime) with high-activated moods during the second half of the workday (assessed at the end of the workday). Moreover, the results of our second supplementary analysis did also not reveal any statistically significant indirect effects. Thus, perceiving techno-support and techno-stress during the morning does not seem to affect high-activated moods during the early and late afternoon.

5.6 Discussion

5.6.1 Theoretical Implications

Drawing on affective events theory, our study aimed to resolve the question of how perceived daily techno-support (i.e., perceived daily support for communication and collaboration and perceived daily ease of effort) and perceived daily techno-stressors (i.e., perceived daily information overload and perceived daily communication overload) affect daily employee innovative behavior through daily high-activated positive mood and daily high-activated negative mood. As predicted by affective events theory and conservation of resources theory, perceived daily support for communication and collaboration and perceived daily ease of effort showed statistically significant positive indirect effects via daily high-activated positive mood. Thus, daily perceived techno-support seems to induce high-activated positive mood which in turn positively affects daily employee innovative behavior. In finding a positive relationship between daily high-activated positive mood and daily employee innovative behavior, we are in line with previous research theorizing and empirically examining innovative behavior to be affect-driven (e.g., Madrid et al., 2014; Montani et al., 2018; Williamson et al., 2019).

Furthermore, we found perceived daily information overload and perceived daily communication overload to negatively affect daily employee innovative behavior through daily high-activated positive mood and, contrary to our expectations, to positively affect that innovative behavior through daily high-activated negative mood. Thus, our results provide support for the proposition of affective events theory (Weiss & Cropanzano, 1996) that affective work events (i.e., daily techno-support and techno-stressors) lead to affective reactions (i.e., positive and negative high-activated moods), which in turn trigger affect-driven behavior (i.e., daily employee innovative behavior).

Moreover, our findings suggest that perceptions of techno-support, which are associated with resource savings (e.g., von Briel et al., 2018), promote high-activated positive mood and that perceptions of techno-stressors, which are associated with resources losses (e.g., Tarafdar et al., 2011), promote high-activated negative mood. Therefore, our results support the assumptions of conservation of resource theory that individuals strive to accumulate resources and to avoid resource losses (Hobfoll, 1989; Ng & Feldman, 2012).

However, we did not find statistically significant indirect relationships between perceived daily support for communication and collaboration and perceived daily ease of effort on the one hand and daily employee innovative behavior on the other hand through daily high-activated negative mood. Our findings indicate that daily techno-support does not reduce daily high-activated negative mood. Rather, the perception of daily techno-stressors seems to reduce daily high-activated positive mood. This could be explained by conservation of resources theory, which proposes that resource losses are more salient than resource gains, an argument based on humans' general tendency to overweight negative or threatening information (Hobfoll, 2001). Thus, while the threat of losing resources resulting from the perception of information and communication overload is so psychologically salient that it increases high-activated negative

mood and reduces high-activated positive mood, the expected resource gains associated with perceiving support for collaboration and communication and an effortless information and feedback retrieval are less salient and consequently only affect high-activated positive mood.

Our results suggest high-activated negative moods trigger rather than hinder the daily innovative behavior of employees. This is in accordance with Montani et al. (2018), who found a positive relationship between general high-activated negative mood and general between-person innovative behavior. This is also in line with conservation of resources theory (Hobfoll, 1989), which states that employees fear resource losses. When they are threatened with resource losses, employees tend to invest their remaining resources in acquiring new ones to offset that potential loss (Hobfoll, 2001). Thus, high-activated negative moods are evoked when employees' resources are threatened as a result of perceiving information and communication overload. High-activated negative mood is characterized by readiness for energy expenditure (Russell, 2003). It thus provides the impetus for employees to invest their remaining resources in performing innovative activities to gain new resources to cope with the loss, for example, in the form of a status improvement within the organization by suggesting ideas leading to performance improvements (Montani et al., 2018).

However, in our supplementary analyses, we did not find relationships between techno-support and techno-stressors perceived in the first half of the workday and high-activated moods during the second half of the workday. Similarly, results of the supplementary analyses revealed non-significant relationships between high-activated moods during the first half of the workday and employee innovative behavior during the second half of the workday. This might be due to the lunch break aiding recovery, replenished resource levels, and psychological detachment from work (Bosch et al., 2018). These have effects on employees' affective states and thus their high-activated moods (Rhee & Kim, 2016). The detachment and recovery experiences could prevent

that perceiving techno-support and techno-stressors as well as high-activated moods during the morning affect high-activated moods and employee innovative behavior, respectively, during the second half of the workday. Additionally, in our supplementary analyses, we did not find perceiving techno-support during the first half of the day to affect high-activated moods during the same period. Contrary to this, perceiving techno-stressors had an impact on high-activated moods during the same period. An explanation for this could be that employees' recovery and resource levels (e.g., energetic and affective resources) are higher in the morning and diminish toward the end of the workday (Binnewies et al., 2009; Sonnentag et al., 2012). An individual's resource pool influences how situations are perceived (Hobfoll, 1989, 2001; Ito & Brotheridge, 2003). Thus, when employees are recovered and full of energy resources (i.e., have a larger resource pool) during the morning, the expected savings of time and energy resources (from perceiving support for communication and collaboration and an effortless retrieval of information and feedback) might not be perceived as that important. However, since individuals particularly fear a loss of resources, these are more salient than potential resource gains (Hobfoll, 2001). Thus techno-stressors have an influence even when employees are full of energy resources.

Our results also suggest that daily employee innovative behavior is determined by perceived daily support for communication and collaboration and perceived daily ease of effort (through daily high-activated positive mood) and perceived daily information and communication overload (through daily high-activated positive and negative moods). In this, we have addressed Orth and Volmer's (2017) call for more research on employees' daily innovative activities and their potential antecedents. In doing so, our findings advance research on the role of digital technologies in innovative processes (Nambisan et al., 2017). Moreover, on the one hand, results showed that digital technologies enable daily employee innovative behavior by triggering high-activated positive and negative moods. On the other hand, digital technologies seem to constrain

daily employee innovative behavior by reducing high-activated positive moods. We thus also answered research calls to examine how digital technologies enable and constrain innovation (Nambisan et al., 2017, 2019).

By instigating high-activated positive moods as well as high-activated negative moods, digital technologies might indeed be a double-edged sword for employees. Consequently, our results support the theorizing of Day et al. (2010) and the results of Diaz et al. (2012) that digital technologies can lead to both employee stress and well-being. However, considering the triggering effect of high-activated negative moods caused by perceiving techno-stressors, digital technologies might not necessarily be a double-edged sword in relation to employee innovative behavior. This is, in turn, in line with the findings of Chandra et al. (2019) who found an inverted u-shaped relationship between techno-stressors and digital-technology-enabled employee innovation. They explain this by using an approach similar to ours also drawing on the conservation of resources theory: With increasing techno-stressors, employees tend to engage less in innovative behavior to conserve their remaining resources. However, when they are facing high levels of techno-stressors, they tend to engage in innovative behavior as a coping mechanism to gain new resources to offset the anticipated resource loss (Chandra et al., 2019). Thus, techno-support and techno-stress might, at least in the short run, both be beneficial for organizations.

5.6.2 Managerial Implications

Our findings may help managers and consultants who want to promote employees' innovative behavior in their organizations. Our results may allow them to better understand why employees are more innovative on specific days and hint at what to do to ensure that employees are innovative when it is particularly needed. We recommend that managers, to promote their

employees' high-activated positive moods and consequently their innovative behavior, ensure that the organization's digital technologies support employees in communicating and collaborating and that they ease the effort of information and feedback retrieval. This could be achieved by providing a modern infrastructure (e.g., fast internet and digital technologies that are state of the art) and reliable, compatible, and thus integrated digital technologies that allow employees to adequately communicate and collaborate and effectively search for information (Day et al., 2010). We also suggest organizations stimulate the sharing of digital-technology-related knowledge and provide training, assistance, and technical support to ensure efficient and effective use of digital technologies (Day et al., 2010; Tarafdar et al., 2011). Organizations could also engage in activities that reduce information and communication overload to prevent an impairment of employees' high-activated positive moods and thus of their innovative behavior. They could take measures that optimize the use of digital technology, including by defining clear rules on when and how to write digital messages, establishing communication guidelines, and questioning response-time expectations and norms (Braukmann et al., 2018; Day et al., 2012). Furthermore, implementing knowledge- and information-management systems might reduce information overload (Karr-Wisniewski & Lu, 2010). Moreover, organizations could provide training to improve employees' abilities to use e-mail features such as filters, to cope with interruptions, and to effectively communicate via digital messages (Basoglu et al., 2009; Day et al., 2010; Soucek & Moser, 2010; Stich et al., 2015).

Our results also hint at the possibility that the perception of daily information and communication overload may foster daily employee innovative behavior through daily high-activated negative mood. Thus, managers may be well advised to be sensitive to their employees' high-activated negative moods. They could offer training on how to convert high-activated negative moods into an impetus for productive, change-oriented activities such as innovative

behaviors (e.g., by increasing their self-regulatory skills) and provide them with time to perform those innovative activities (Montani et al., 2018). However, experiencing high-activated negative moods over an extended period could negatively affect employees' health (Spector & Goh, 2001). Consequently, in the long run, it is important that managers adopt measures to reduce information and communication overload and make sure that employees do not need to use innovative behavior as a strategy to cope with and overcome difficult, emotionally upsetting work conditions.

5.6.3 Limitations and Implications for Future Research

As with every study, ours has limitations that offer avenues for future research. First, we relied on self-reported measures from the same person, which could induce the problem of common method bias (Podsakoff et al., 2003). However, our single-factor test (Korsgaard & Roberson, 1995; Mossholder et al., 1998; Podsakoff et al., 2003) suggests that results should not be substantially affected by common method bias. Furthermore, we included high-activated moods in our analyses and controlled for positive and negative trait affect, which serves as an additional means to contain common method variance (Gabriel et al., 2019; Podsakoff et al., 2003). Nevertheless, future research could account for the common method bias problem and try to replicate our findings by using different data sources for the mediators or the dependent variable. As supervisors or peers may not be able to observe and evaluate day-to-day changes, this might not be feasible in relation to daily employee innovative behavior (Binneswies & Wörnlein, 2011). However, researchers might use technologies and thus physiological methods to measure high-activated moods (Williamson et al., 2019).

Second, we only analyzed the effects of digital-technology-related affective work events that happened during the actual workday. However, research (see, e.g., Braukmann et al., 2018;

Tarafdar et al., 2011) indicates that there might be positive and negative affective events that happen during nonwork hours and which could also have an effect on daily employee innovative behavior. For example, being able to continue or complete work tasks from home or being able to help colleagues due to being available are potential positive events. Examples of negative affective events include invasion of private space due to e-mails or other instant messages after hours with the expectation of an immediate reply (Braukmann et al., 2018; Tarafdar et al., 2011). For example, Braukmann et al. (2018) found digital-technology-related negative affective events that happened after hours negatively affected sleep quality, which is a predictor of daily high-activated moods and innovative behavior (Williamson et al., 2019). Thus, future studies could examine the relationships between daily digital-technology-related affective events that happen after actual working time and daily employee innovative behavior.

Third, we did not examine moderator variables. However, affective events theory suggests that the relationships between digital-technology-related daily work events and employees' affective reactions might be strengthened or weakened by their personal dispositions (Weiss & Cropanzano, 1996). Thus, future studies could examine individual characteristics as potential moderators. Previous research suggests that digital-technology-related self-efficacy, the judgment of one's ability to use digital technologies (Compeau & Higgins, 1995), might affect employees' affective reactions to perceiving daily techno-support and daily techno-stressors. That self-efficacy might have an effect on employees' affective reactions to digital-technology-related work events in the form of techno-support because employees with high digital-technology-related self-efficacy understand the benefits of being supported by digital technologies (Hung, 2003). Moreover, digital-technology-related self-efficacy has been found to buffer the effect of techno-stressors on negative affective responses (J. Wu et al., 2017). Thus, such self-efficacy

might affect employees' mood reactions to perceiving daily information and communication overload.

Fourth, perceptions of techno-support and techno-stressors might differ between employees with different work arrangements (Day et al., 2012). For example, employees that work in virtual teams or do telework should particularly rely on being supported in communicating and collaborating with their colleagues. They may also be particularly prone to digital-technology-induced information and communication overload because they mainly communicate via digital technologies (Day et al., 2010; Gillam & Oppenheim, 2006; Suh & Lee, 2017). Therefore, their affective responses to the digital-technology-related work events that we analyzed in our study might differ. Thus, future studies could examine whether the effects of perceived daily techno-support and perceived daily techno-stressors on daily employee innovative behavior via daily high-activated moods differ between employees with different work arrangements.

5.7 Conclusion

Our study examined how perceived daily techno-support and perceived daily techno-stressors affect daily employee innovative behavior. In doing so, it sheds more light on the determinants of employees' daily innovative activities. Drawing on affective events theory and conservation of resources theory, we showed that digital technologies might not necessarily be a double-edged sword regarding employee innovative behavior. Perceived daily techno-support had a positive indirect effect on daily employee innovative behavior through daily high-activated positive mood. On the one hand, perceived daily techno-stressors negatively affected daily employee innovative behavior through daily high-activated positive mood. On the other hand, we also found a positive indirect effect via daily high-activated negative mood. Therefore, results

indicate that at least in the short run, both perceiving techno-support and techno-stressors might trigger employees' innovative activities and thus benefit organizations.

6. Overall Discussion and Implications for Research and Practice

This thesis' objective is to examine and explain the role that digital technologies play regarding employee intrapreneurial and innovative behavior. To do so, four independent empirical studies were conducted. The first study (see Chapter 2) analyzed how and why digital affordances (i.e., generativity and disintermediation) influenced employee intrapreneurial behavior (reflected by employee corporate entrepreneurship participation likelihood). The second study (see Chapter 3) examined if support by digital technologies (i.e., support by collaborative technologies, social media, and intelligent decision support systems) contributes to employee intrapreneurial behavior (reflected by employee corporate entrepreneurship participation likelihood and employee likelihood of intrapreneurial behavior). It also examined how this relationship is influenced by management support for innovation as an organizational resource and intrapreneurial self-efficacy as a personal resource. The third study (see Chapter 4) explored employee techno-work engagement and employee-perceived techno-strain as mediators of the relationships between the digital technology characteristics employee-perceived digital technology usefulness and employee-perceived digital technology complexity on the one hand and employee innovative performance on the other hand. Finally, the fourth study (see Chapter 5) examined daily employee innovative behavior. It addressed the question of how perceived daily techno-support (reflected by perceived daily support for communication and collaboration and perceived daily ease of effort) and perceived daily techno-stressors (reflected by perceived daily information overload and perceived daily communication overload) influence daily employee innovative behavior. It explored how these relationships are mediated by daily high-activated positive mood and daily high-activated negative mood. The results of the four studies outlined in this thesis are summarized in the following section.

6.1 Summary of the Study Results

The first study found positive indirect effects of both generativity and disintermediation on employee corporate entrepreneurship participation likelihood through employee-perceived IT support for innovation. The direct relationships between generativity and disintermediation and employee-perceived IT support for innovation and between employee-perceived IT support for innovation and employee corporate entrepreneurship participation likelihood were also positive. Surprisingly, results showed a positive indirect effect of digital affordances on employee corporate entrepreneurship participation likelihood through employee-perceived work overload. As the direct relationships of both generativity and disintermediation with employee-perceived work overload were negative, results indicate that digital affordances reduce employee-perceived workload and, in this context, lead to resource gains rather than losses. Nevertheless, the direct relationship between employee-perceived work overload and employee corporate entrepreneurship participation likelihood was still negative. There was no statistically significant indirect effect of digital affordances on employee corporate entrepreneurship participation likelihood through employee-perceived invasion of privacy. While results revealed a positive relationship between generativity and employee-perceived invasion of privacy, disintermediation's relationship with employee-perceived invasion of privacy was not statistically significant. Finally, employee-perceived invasion of privacy and employee corporate entrepreneurship participation likelihood were also not statistically significantly related.

In the second study, direct effects of support by collaborative technologies, support by social media, and support by intelligent decision support systems on both employee corporate entrepreneurship participation likelihood and employee likelihood of intrapreneurial behavior, which better reflected the agentic and proactive nature of employee intrapreneurial behavior, were

found. However, our results revealed differences between the two types of employee intrapreneurial behavior in relation to the moderating role of the organizational resource management support for innovation and the personal resource intrapreneurial self-efficacy. Management support for innovation positively moderated the effects of support by collaborative technologies and support by intelligent decision support systems on employee likelihood of intrapreneurial behavior. However, it only strengthened the relationship between support by collaborative technologies and employee corporate entrepreneurship participation likelihood. Furthermore, regarding employee corporate entrepreneurship participation likelihood, there was no evidence of any significant two-way interactions between support by digital technologies and intrapreneurial self-efficacy. For employee likelihood of intrapreneurial behavior, the relationships with support by collaborative technologies and support by social media were found to be strengthened by intrapreneurial self-efficacy. Finally, results only revealed a marginally significant three-way interaction effect between support by collaborative technologies, management support for innovation, and intrapreneurial self-efficacy on employee corporate entrepreneurship participation likelihood. All other hypothesized three-way interactions were not statistically significant.

The third study identified a positive indirect effect of the digital-technology-related job resource employee-perceived digital technology usefulness on employee innovative performance through employee techno-work engagement. However, no indirect effect of the digital-technology-related job demand employee-perceived digital technology complexity on employee innovative performance through employee-perceived techno-strain was found. Employee-perceived complexity was negatively related to employee-perceived digital technology usefulness. Moreover, employee-perceived techno-strain was negatively related to employee techno-work engagement and negatively related to employee innovative performance through employee techno-work

engagement. The direct relationship between employee-perceived techno-strain and employee innovative performance, in contrast, was not statistically significant. Employee-perceived digital technology usefulness and employee-perceived techno-strain were found to mediate the relationship between employee-perceived digital technology complexity and employee techno-work engagement such that the indirect effects were negative. The third study also showed the relationship between employee-perceived digital technology complexity and employee innovative performance to be sequentially mediated by employee-perceived digital technology usefulness as well as employee-perceived techno-strain and employee techno-work engagement such that the indirect effects were negative.

Finally, the fourth study found a positive indirect effect of perceived daily support for communication and collaboration and perceived daily ease of effort on daily employee innovative behavior through daily high-activated positive mood. While both types of perceived daily techno-support were positively related to daily high-activated positive mood, they were not statistically significantly related to daily high-activated negative mood. Hence, results did not reveal an indirect effect of perceived daily support for communication and collaboration and perceived daily ease of effort on daily employee innovative behavior through daily high-activated negative mood. Regarding perceived daily techno-stressors, perceived daily information overload and perceived daily communication overload were both negatively related to daily high-activated positive mood and positively related to daily high-activated negative mood. Furthermore, perceived daily information overload and perceived daily communication overload both had a negative indirect effect on daily employee innovative behavior through daily high-activated positive mood. Surprisingly both also had a positive indirect effect via daily high-activated negative mood. Thus, while daily high-activated positive mood had a positive relationship with daily employee

innovative behavior, results revealed daily high-activated negative mood was also positively related to this behavior.

6.2 Theoretical Implications

Conducting four empirical studies, this thesis sheds more light on the role of digital technologies regarding employee intrapreneurial and innovative behavior. On the one hand, this was done by examining the mechanisms through which digital technologies foster and inhibit these behaviors. On the other hand, this involved analyzing how the fostering role of digital technologies for employee intrapreneurial behavior is influenced by organizational and individual characteristics. With this, the thesis contributes to the digital entrepreneurship and innovation literature, which has been largely conceptual so far, has mainly concentrated on how digital technologies create opportunities for entrepreneurship and innovation, and has paid little attention to how these technologies impact employee intrapreneurial and innovative behavior. The thesis also advances general intrapreneurship literature since the findings provide insights on how to encourage the likelihood of employee engagement in intrapreneurial activities (Kuratko, Hornsby, & Hayton, 2015). The thesis also adds to pioneer studies such as the ones conducted by Baum and Rabl (2019) and Junglas et al. (2019). These studies found an organization's digital capital to stimulate employee corporate entrepreneurship decisions (Baum & Rabl, 2019) and the use of consumer digital technologies to positively affect employee innovative behavior (Junglas et al., 2019). However, this thesis goes beyond these studies. It takes a closer look at how digital technologies foster employee intrapreneurial and innovative behavior. But it also examines the influence on these behaviors of potential negative consequences associated with the use of these digital technologies. Moreover, it provides an analysis of how the interplay of organizational and

personal resources¹¹ influences the relationship between digital technology support and employee intrapreneurial behavior.

This thesis also adds further empirical evidence to the theorizing and findings on the double-edged sword that digital technologies constitute for employees (see, e.g., J. R. Carlson et al., 2017; Day et al., 2010; Diaz et al., 2012; Tarafdar et al., 2019) and their innovative behavior (Chandra et al., 2019). It provides answers to the questions posed by Nambisan et al. (2017) on how digital technologies and digital infrastructures enable and constrain innovation and on how the use of digital-technology infrastructures constrains or enables the participation in innovation.

The results indicate that the potentials for resource gains offered by the use of digital technologies might be beneficial and that organizational resources such as management support for innovation strengthen the relationship between digital technology support and employee intrapreneurial behavior. The thesis therefore enhances our understanding of how the internal organizational environment affects employee intrapreneurial behavior, thus answering Rigtering et al.'s (2019) call.

By taking a resource perspective on how digital technologies foster and inhibit employee intrapreneurial and innovative behavior, we build on recent research by Gawke et al. (2017, 2018) and their demands-resources perspective on the consequences of employee intrapreneurial behavior. Conservation of resources theory (Hobfoll, 1989, 2001), which is used as a theoretical framework in the studies outlined in Chapters 2, 3, and 5, has mainly been applied to predict stress outcomes. Scholars have only recently begun to draw on this theory to investigate the implications of resource gains and losses for motivational outcomes (Hobfoll et al., 2018). In this

¹¹ Baum and Rabl (2019) examined how the relationship between an organization's digital capital and employee corporate entrepreneurship decisions is influenced by the interplay of ability- and motivation-related personal resources.

thesis, conservation of resources theory is successfully applied to analyze how the resource gains and losses stemming from digital affordances affect employee intrapreneurial behavior and how the relationship between digital technology support and that behavior is influenced by additional organizational and personal resources. Thus, it is shown that conservation of resources theory is also suitable to predict employees' intrapreneurial activities, which is something it has not yet been applied to do. With this, the thesis contributes to both intrapreneurship research and the literature on the conservation of resources theory. It also adds to those literature streams by introducing digital-technology-related support resources (employee-perceived IT support for innovation, support by collaborative technologies, support by social media, support by intelligent decision support systems, perceived daily support for communication and collaboration, and perceived daily ease of effort) and perceptions of the usefulness of the digital technologies at one's workplace as important resources for employee intrapreneurial and innovative behavior. Additionally, the thesis adds to previous research by Chandra et al. (2019), who used conservation of resources theory to explain the curvilinear relationship between techno-stress creators and digital-technology-enabled employee innovation. Besides that, by successfully applying a resource perspective on the role of digital technologies regarding employees' intrapreneurial and innovative behavior and thus by theorizing on and empirically examining the potential for resource gains offered by the use of digital technologies' positive relationships with employee intrapreneurial and innovative behavior, this thesis' results also provide support for von Briel et al.'s (2018) resource-based theoretical arguments on the enabling mechanisms of digital technologies in the creation of new ventures.

This thesis adds to our understanding of the motivational responses to the potentials for resource gains and losses offered by the use of digital technologies. Results of the third study, which used the job demands-resources model (Bakker & Demerouti, 2007, 2017; Demerouti et al.,

2001) as a theoretical framework, suggest that digital-technology-related job resources lead to employee techno-work engagement, which fosters employee innovative behavior. Findings also showed that digital-technology-related job demands might negatively affect that innovative behavior as they lead to employee-perceived techno-strain, which is detrimental to employee techno-work engagement. In addition, the results indicate that the daily use of digital technology results in daily high-activated positive and negative mood, both of which foster daily employee innovative behavior. Thus, this thesis shows that motivational effects are important in the relationship between the use of digital technology and employee innovative behavior. By analyzing the motivational responses to the potentials for resource gains and losses offered by the use of digital technologies, we were able to answer J. R. Carlson et al.'s (2017) call to examine various motivational constructs and their relationship to technologies.

6.3 Managerial Implications

This thesis' findings may help managers and consultants better understand the role that digital technologies play regarding employee intrapreneurial and innovative behavior. Managers that want to encourage those behaviors are well-advised to invest in their organization's digital-technology infrastructure. They should make sure that this digital-technology infrastructure supports employees' tasks to reach high usefulness perceptions and that it provides the potential for generativity and disintermediation. In doing so, managers may also be able to ensure that the digital technologies support employee communication and collaboration and an effortless retrieval of information and feedback.

However, practitioners should also be aware of the negative consequences that come along with using digital technologies. Having to use complex digital technologies could lead to techno-strain, which negatively affects employee innovative performance via a reduction of their techno-

work engagement. Furthermore, employees' daily perceptions of techno-stressors are on the one hand detrimental to their high-activated positive moods and thus negatively impact their innovative behavior. On the other hand, they are triggers of high-activated negative moods, which may be beneficial for employee innovative behavior in the short run, but might threaten long-term employee health (Spector & Goh, 2001). To attenuate the negative consequences of digital technologies in relation to employee health and their intrapreneurial and innovative behavior, organizations could offer training to improve the abilities of employees in using those technologies (Shu et al., 2011). They could also offer support in the form of providing a competent help-desk, the latest digital technologies, and required updates, as well as promoting knowledge-sharing and employees' involvement in digital-technology decisions (Day et al., 2012; Tarafdar et al., 2015).

6.4 Limitations and Implications for Future Research

The limitations of this thesis provide avenues for future research, which are elaborated in this section. First, this thesis does not account for cyclical relationships and possible backward influences that may result from engaging in intrapreneurial and innovative behavior on employee perceptions of the potentials for resource gains and losses offered by the use of digital technologies. However, for example, previous research has found that engaging in intrapreneurial behavior might lead to gains in personal resources (Gawke et al., 2017) but might also cause exhaustion due to the required resource investments (Gawke et al., 2018). Thus, as an individual's resource pool influences how situations are defined (Ito & Brotheridge, 2003), this might have an effect on the evaluation of the potentials for resource gains and losses associated with using the digital technologies at one's workplace and consequently could have an impact on subsequent decisions on continuing intrapreneurial activities and/or on whether to engage in these again. Similarly, intrapreneurial and innovative activities might also result in the creation of new

digital technologies (Lyytinen et al., 2016; Steininger, 2019) or in digital-technology-induced work improvements (Junglas et al., 2019). These might also affect the perceptions of the potentials for resource gains and losses stemming from the use of digital technologies. Future research could explore how the outcomes of engaging in intrapreneurial or innovative behaviors may, in turn, influence the perceptions of the potentials for resource gains and losses offered by the use of digital technologies. Moreover, investigating how these outcomes influence employees' subsequent intrapreneurial or innovative behaviors might also be an interesting avenue of inquiry.

Second, the participants in all four studies were employees from organizations in Germany. Digital-technology infrastructure and access (Hanafizadeh et al., 2009) and employee protection, worktime regulations, and attitudes toward overtime all differ between countries (Wharton & Blair-Loy, 2002). Thus, the perceptions of the potentials for resource gains and losses may also vary. To account for these differences and to increase the generalizability of the findings, future research should recruit participants from organizations in other nations and compare different country samples.

Third, virtual-work arrangements such as telework or virtual teams are increasingly used in organizations (Raghuram et al., 2019). However, in all four studies that are outlined in this thesis, no data was collected on whether respondents participated in such arrangements. Employees that mainly work and communicate via digital technologies should particularly benefit from potential resource gains and be particularly sensitive to potential resource losses from the use of digital technologies (Day et al., 2010; Gillam & Oppenheim, 2006; Suh & Lee, 2017). Future research might account for this and examine if participating in virtual-work arrangements influences the findings in this thesis.

Fourth, previous research (Day et al., 2012) has found that organizational resources in the form of support for the use of digital technologies could buffer the negative effects of the resource losses associated with using digital technologies. Hence, future research might analyze if organizational support for the use of digital technologies weakens the negative effects of the potentials for resource losses associated with the use of the digital technologies at one's workplace and thus influences the role of those technologies regarding employee intrapreneurial and innovative behavior.

Fifth, in this thesis, only the moderating role of intrapreneurial self-efficacy as an intrapreneurship-related personal resource was investigated. However, other personal resources might also affect employee perceptions of the potentials for resource gains and losses offered by the use of digital technologies and thus possibly influence decisions on whether to engage in intrapreneurial or innovative activities. Digital-technology-related personal resources (e.g., digital-technology-related self-efficacy and digital fluency) allow employees to choose and use digital technologies in accordance with their goals and to understand the benefits of that use (Briggs & Makice, 2012; Hung, 2003). Employees with high digital-technology-related personal resources should be more likely to perceive the potentials for resource gains and less likely to perceive the potentials for resource losses associated with the use of the digital technologies at their workplaces. However, Baum and Rabl (2019) suggest that it is not only ability-related personal resources (e.g., intrapreneurial self-efficacy, digital-technology-related self-efficacy, or digital fluency) that are relevant. Motivation-related personal resources might also influence employee perceptions of the consequences of using digital technologies. Personal initiative is an example of such a personal resource (Ocampo & Reyes, 2016). Individuals with higher levels of personal initiative are proactive and able to think of alternative ways to do a task (Frese et al., 1996). Proactive employees identify opportunities and act on them (Crant, 1996). Thus, they

should be more likely to recognize the potentials for resource gains offered by the use of digital technologies. An employee's need for achievement is another motivation-related personal resource (Barreiro & Treglown, 2020; Han et al., 2014) that aids employees in recognizing opportunities (Hanohov & Baldacchino, 2018; Shane et al., 2003). Employees with a high need for achievement should also be more prone to recognize the potentials for resource gains offered by the use of digital technologies. Furthermore, Baum and Rabl's (2019) findings indicate that digital technologies are particularly recognized as opportunities that ease intrapreneurial activities when employees are high in both ability- and motivation-related personal resources. Future research could examine whether the perceptions of the potentials for resource gains and losses offered by the use of digital technologies and their effects on the intrapreneurial and innovative behavior of employees are influenced by ability-related personal resources that capture an employee's ability to use digital technologies and by motivation-related personal resources. Such research could also investigate how these perceptions are affected by the interplay of those ability- and motivation-related personal resources.

7. Conclusion

Based on a resource perspective, this thesis' objective is elucidating how digital technologies foster and inhibit employee intrapreneurial and innovative behavior. To do so, four empirical studies were conducted that targeted three research questions. First, the thesis aimed at answering the question of what role do the potentials for resource gains and losses offered by the use of digital technologies play regarding employee intrapreneurial and innovative behavior. The findings revealed that digital affordances positively influence employee corporate entrepreneurship participation likelihood through resource gains in the form of employee-perceived IT support for innovation and a reduction of resource losses in the form of reduced work overload perceptions. Although generativity was found to be positively related to employee perceptions of privacy invasion, digital affordances did not have an indirect relationship with employee corporate entrepreneurship participation likelihood through those perceptions. Thus, digital affordances seem to play a beneficial role in employee intrapreneurial behavior by offering resource gains rather than being detrimental to it by offering resource losses.

Furthermore, potentials for resource gains in the form of digital technology support were found to stimulate employee intrapreneurial behavior. Results showed a positive indirect effect of employee-perceived digital technology usefulness and negative sequential indirect effects of employee-perceived digital technology complexity on employee innovative performance. Beyond that, while perceived daily techno-support had positive indirect influences on daily employee innovative behavior, perceived daily techno-stressors had both positive and negative indirect effects on employee's daily innovative activities. Thus, potentials for resource gains in the form of useful digital technologies, daily support for communication and collaboration, and daily ease of effort of information and feedback retrieval seem to play a beneficial role regarding employee

innovative behavior. While potentials for resource losses in the form of complex digital technologies appear to be detrimental to employee innovative behavior, results indicate that daily information and communication overload could both foster and inhibit that behavior.

Second, the thesis addressed the question of how do additional organizational and personal resources moderate the relationship between digital technology support (as an example of the potentials for resource gains offered by the use of digital technologies) and employee intrapreneurial behavior. The relative impact of the support by different digital technologies varied with different levels of organizational resources in the form of management support for innovation and personal resources in the form of intrapreneurial self-efficacy. Management support for innovation seems to strengthen the positive relationship between support by collaborative technologies and both the likelihood of employees to initiate and advance an intrapreneurial project on their own accord and their likelihood to participate in such a project. Management support for innovation also strengthens the effect of support by intelligent decision support systems on employees' likelihood to initiate and advance an intrapreneurial project on their own accord. Intrapreneurial self-efficacy fueled the relationship between support by collaborative technologies and support by social media and employee's likelihood to initiate and advance an intrapreneurial project on their own accord. Finally, a joint fueling effect of organizational and personal resources was only found for the relationship between support by collaborative technologies and employee likelihood to participate in an intrapreneurial project. However, this effect was only marginally significant.

Third, the thesis aimed at answering the question of what mediating role do the motivational responses to the potentials for resource gains and losses offered by the use of digital technologies play in the relationship with employee innovative behavior. Employee-perceived digital technology usefulness had a positive indirect effect on employee innovative performance

through the motivational construct of employee techno-work engagement. Furthermore, employee-perceived digital technology complexity only indirectly affected employee innovative performance by reducing employee techno-work engagement. The findings revealed positive indirect relationships between perceived daily techno-support and daily employee innovative behavior through employees' daily high-activated positive moods. Perceived daily techno-stressors had negative indirect relationships with daily employee innovative behavior through daily high-activated positive mood and positive indirect relationships through daily high-activated negative mood.

Thus, findings indicate that by having the potential to induce both resource gains and losses, digital technologies might be a double-edged sword for employee intrapreneurial and innovative behavior. However, results on the one hand disclosed a positive indirect relationship between digital affordances and employee corporate entrepreneurship participation likelihood through employee-perceived work overload. On the other hand, positive indirect relationships were found between perceived daily techno-stressors and daily employee innovative behavior through daily high-activated negative mood. The results thus revealed more positive effects than expected. Managers that want to foster employee intrapreneurial and innovative behavior are recommended to invest in their digital-technology infrastructure. However, this could introduce negative consequences with the potential to inhibit employee engagement in intrapreneurial and innovative activities. As such, accompanying measures are needed that counteract these adverse effects, such as, for example, providing training or organizational support.

Appendix

Variables Manipulated in the Conjoint Profiles in the Second Study

Parameter	Level	Description
Support by collaborative technologies	Present	For the collaboration in the project, <u>collaborative technologies</u> (e.g., instant messaging services, project management systems, work and task management systems) <u>can be used</u> .
	Not present	For the collaboration in the project, <u>collaborative technologies</u> (e.g., instant messaging services, project management systems, work and task management systems) <u>cannot be used</u> .
Support by social media	Present	<u>It is possible to use social media</u> (e.g., social networks, blogs, content communities) in the course of the project.
	Not present	<u>It is not possible to use social media</u> (e.g., social networks, blogs, content communities) in the course of the project.
Support by intelligent decision support systems	Present	For the project work, <u>intelligent decision support systems</u> (e.g., intelligent predictive systems, text mining, machine learning) <u>can be consulted</u> .
	Not present	For the project work, <u>intelligent decision support systems</u> (e.g., intelligent predictive systems, text mining, machine learning) <u>cannot be consulted</u> .
Management support for innovation	High	Management facilitates and promotes employees' innovative behavior <u>to a large degree by strongly championing innovative ideas and providing the resources required to take innovative actions</u> .
	Low	Management facilitates and promotes employees' innovative behavior <u>to a minor degree by weakly championing innovative ideas and hardly providing the resources required to take innovative actions</u> .

References

- Acharya, P., & Taylor, R. (2012). Innovative deviance: An investigation of the relationships between social control, creativity and innovation in organizations. *Academy of Business Research Journal*, 1(1), 49–58. <https://ssrn.com/abstract=2519799>
- Adamides, E. D., & Karacapilidis, N. (2006). Information technology support for the knowledge and social processes of innovation management. *Technovation*, 26(1), 50–59. <https://doi.org/10.1016/j.technovation.2004.07.019>
- Addas, S., & Pinsonneault, A. (2018). E-mail interruptions and individual performance: Is there a silver lining? *MIS Quarterly*, 42(2), 381–406. <https://doi.org/10.25300/MISQ/2018/13157>
- Aguinis, H., & Bradley, K. J. (2014). Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organizational Research Methods*, 17(4), 351–371. <https://doi.org/10.1177/1094428114547952>
- Ahmad, N., & Abdulkarim, H. (2019). The impact of flow experience and personality type on the intention to use virtual world. *International Journal of Human-Computer Interaction*, 35(12), 1074–1085. <https://doi.org/10.1080/10447318.2018.1509500>
- Ahuja, M. K., Chudoba, K. M., Kacmar, C. J., McKnight, D. H., & George, J. F. (2007). IT road warriors: Balancing work-family conflict, job autonomy, and work overload to mitigate turnover intentions. *MIS Quarterly*, 31(1), 1–17. <https://doi.org/10.2307/25148778>
- Aiman-Smith, L., Scullen, S. E., & Barr, S. H. (2002). Conducting studies of decision making in organizational contexts: A tutorial for policy-capturing and other regression-based techniques. *Organizational Research Methods*, 5(4), 388–414. <https://doi.org/10.1177/109442802237117>

- Alge, B. J. (2001). Effects of computer surveillance on perceptions of privacy and procedural justice. *Journal of Applied Psychology*, 86(4), 797–804. <https://doi.org/10.1037/0021-9010.86.4.797>
- Allen, M. W., Coopman, S. J., Hart, J. L., & Walker, K. L. (2007). Workplace surveillance and managing privacy boundaries. *Management Communication Quarterly*, 21(2), 172–200. <https://doi.org/10.1177/0893318907306033>
- Alpkan, L., Bulut, C., Gunday, G., Ulusoy, G., & Kilic, K. (2010). Organizational support for intrapreneurship and its interaction with human capital to enhance innovative performance. *Management Decision*, 48(5), 732–755. <https://doi.org/10.1108/00251741011043902>
- Amabile, T. M. (1988). A model of creativity and innovation in organizations. In B. M. Staw & L. L. Cummings (Eds.), *Research in organizational behavior* (Vol. 10, pp. 123–167). JAI Press.
- Amit, R., & Han, X. (2017). Value creation through novel resource configurations in a digitally enabled world. *Strategic Entrepreneurship Journal*, 11(3), 228–242. <https://doi.org/10.1002/sej.1256>
- Anderson, N., de Dreu, C. K., & Nijstad, B. A. (2004). The routinization of innovation research: A constructively critical review of the state-of-the-science. *Journal of Organizational Behavior*, 25(2), 147–173. <https://doi.org/10.1002/job.236>
- Anderson, N., Potočník, K., & Zhou, J. (2014). Innovation and creativity in organizations: A state-of-the-science review, prospective commentary, and guiding framework. *Journal of Management*, 40(5), 1297–1333. <https://doi.org/10.1177/0149206314527128>

- Antonicic, B., & Hisrich, R. D. (2003). Clarifying the intrapreneurship concept. *Journal of Small Business and Enterprise Development*, 10(1), 7–24. <https://doi.org/10.1108/14626000310461187>
- Ardito, L., Messeni Petruzzelli, A., & Albino, V. (2015). From technological inventions to new products: A systematic review and research agenda of the main enabling factors. *European Management Review*, 12(3), 113–147. <https://doi.org/10.1111/emre.12047>
- Arthur, R. (2014, October 24). How Hermès is winning with creative online content. *Forbes*. <http://www.forbes.com/sites/rachelarthur/2014/10/24/how-hermes-is-winning-with-creative-online-content/>
- Arvidsson, V., & Mønsted, T. (2018). Creating innovation potential: How digital entrepreneurs conceal, sequence, anchor and propagate new technology. *Journal of Strategic Information Systems*, 27(4), 369–383. <https://doi.org/10.1016/j.jsis.2018.10.001>
- Atzmüller, C., & Steiner, P. M. (2010). Experimental vignette studies in survey research. *Methodology*, 6(3), 128–138. <https://doi.org/10.1027/1614-2241/a000014>
- Autio, E., Nambisan, S., Thomas, L. D., & Wright, M. (2018). Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal*, 12(1), 72–95. <https://doi.org/10.1002/sej.1266>
- Autio, E., Pathak, S., & Wennberg, K. (2013). Consequences of cultural practices for entrepreneurial behaviors. *Journal of International Business Studies*, 44(4), 334–362. <https://doi.org/10.1057/jibs.2013.15>
- Axtell, C. M., Holman, D. J., Unsworth, K. L., Wall, T. D., Waterson, P. E., & Harrington, E. (2000). Shopfloor innovation: Facilitating the suggestion and implementation of ideas. *Journal of Occupational and Organizational Psychology*, 73(3), 265–285. <https://doi.org/10.1348/096317900167029>

- Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: Technological antecedents and implications. *MIS Quarterly*, 35(4), 831–858. <https://doi.org/10.2307/41409963>
- Bafoutsou, G., & Mentzas, G. (2002). Review and functional classification of collaborative systems. *International Journal of Information Management*, 22(4), 281–305. [https://doi.org/10.1016/S0268-4012\(02\)00013-0](https://doi.org/10.1016/S0268-4012(02)00013-0)
- Bagozzi, R. P., & Baumgartner, H. (1994). The evaluation of structural equation models and hypothesis testing. In R. P. Bagozzi (Ed.), *Principles of marketing research* (pp. 386–422). Blackwell.
- Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, 16(1), 74–94. <https://doi.org/10.1007/BF02723327>
- Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of Managerial Psychology*, 22(3), 309–328. <https://doi.org/10.1108/02683940710733115>
- Bakker, A. B., & Demerouti, E. (2017). Job demands-resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology*, 22(3), 273–285. <https://doi.org/10.1037/ocp0000056>
- Bakker, A. B., Demerouti, E., de Boer, E., & Schaufeli, W. B. (2003). Job demands and job resources as predictors of absence duration and frequency. *Journal of Vocational Behavior*, 62(2), 341–356. [https://doi.org/10.1016/S0001-8791\(02\)00030-1](https://doi.org/10.1016/S0001-8791(02)00030-1)
- Bakker, A. B., Demerouti, E., Taris, T. W., Schaufeli, W. B., & Schreurs, P. J. G. (2003). A multigroup analysis of the job demands-resources model in four home care organizations. *International Journal of Stress Management*, 10(1), 16–38. <https://doi.org/10.1037/1072-5245.10.1.16>

- Bakker, A. B., Demerouti, E., & Verbeke, W. (2004). Using the job demands-resources model to predict burnout and performance. *Human Resource Management*, 43(1), 83–104.
<https://doi.org/10.1002/hrm.20004>
- Bakker, A. B., Tims, M., & Derks, D. (2012). Proactive personality and job performance: The role of job crafting and work engagement. *Human Relations*, 65(10), 1359–1378.
<https://doi.org/10.1177/0018726712453471>
- Bakos, Y. (1998). The emerging role of electronic marketplaces on the internet. *Communications of the ACM*, 41(8), 35–42. <https://doi.org/10.1145/280324.280330>
- Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist*, 28(2), 117–148. https://doi.org/10.1207/s15326985ep2802_3
- Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.
- Barber, L. K., Grawitch, M. J., & Munz, D. C. (2013). Are better sleepers more engaged workers? A self-regulatory approach to sleep hygiene and work engagement. *Stress and Health*, 29(4), 307–316. <https://doi.org/10.1002/smi.2468>
- Barber, L. K., & Santuzzi, A. M. (2015). Please respond ASAP: Workplace telepressure and employee recovery. *Journal of Occupational Health Psychology*, 20(2), 172–189.
<https://doi.org/10.1037/a0038278>
- Barley, S. R., Meyerson, D. E., & Grodal, S. (2011). E-mail as a source and symbol of stress. *Organization Science*, 22(4), 887–906. <https://doi.org/10.1287/orsc.1100.0573>
- Barreiro, C. A., & Treglown, L. (2020). What makes an engaged employee? A facet-level approach to trait emotional intelligence as a predictor of employee engagement. *Personality and Individual Differences*, 159, Article 109892. <https://doi.org/10.1016/j.paid.2020.109892>

- Basoglu, K. A., Fuller, M. A., & Sweeney, J. T. (2009). Investigating the effects of computer mediated interruptions: An analysis of task characteristics and interruption frequency on financial performance. *International Journal of Accounting Information Systems*, 10(4), 177–189. <https://doi.org/10.1016/j.accinf.2009.10.003>
- Baum, M., & Rabl, T. (2019). Digital capital as an opportunity-enhancer for employee corporate entrepreneurship decisions. In H. Krcmar, J. Fedorowicz, W. F. Boh, J. M. Leimeister, & S. Wattal (Eds.), *Proceedings of the 40th International Conference on Information Systems* (Vol. 5, pp. 3791–3807). Association for Information Systems. https://aisel.aisnet.org/icis2019/innov_entre/innov_entre/1/
- Bawden, D., & Robinson, L. (2009). The dark side of information: Overload, anxiety and other paradoxes and pathologies. *Journal of Information Science*, 35(2), 180–191. <https://doi.org/10.1177/0165551508095781>
- Behrens, J., & Patzelt, H. (2016). Corporate entrepreneurship managers' project terminations: Integrating portfolio-level, individual-level, and firm-level effects. *Entrepreneurship Theory and Practice*, 40(4), 815–842. <https://doi.org/10.1111/etap.12147>
- Beierlein, C., Kovaleva, A., Kemper, C. J., & Rammstedt, B. (2014). *Eine Single-Item-Skala zur Erfassung von Risikobereitschaft: Die Kurzskala Risikobereitschaft-1 (R-1)* [A single-item scale to assess the willingness to take risks: The short scale willingness to take risk-1 (R-1)] (GESIS-Working Papers, 2014/34). GESIS -Leibniz-Institut für Sozialwissenschaften. https://www.gesis.org/fileadmin/kurzskalen/working_papers/R1_WorkingPapers_2014-34_alt.pdf
- Bélanger, F., & Allport, C. D. (2008). Collaborative technologies in knowledge telework: An exploratory study. *Information Systems Journal*, 18(1), 101–121. <https://doi.org/10.1111/j.1365-2575.2007.00252.x>

- Bennett, A. A., Bakker, A. B., & Field, J. G. (2018). Recovery from work-related effort: A meta-analysis. *Journal of Organizational Behavior*, 39(3), 262–275. <https://doi.org/10.1002/job.2217>
- Bhatt, G. D., Gupta, J. N. D., & Kitchens, F. (2005). An exploratory study of groupware use in the knowledge management process. *Journal of Enterprise Information Management*, 18(1), 28–46. <https://doi.org/10.1108/17410390510571475>
- Bhattacharjee, A. (2001). Understanding information systems continuance: An expectation–confirmation model. *MIS Quarterly*, 25(3), 351–370. <https://doi.org/10.2307/3250921>
- Bindl, U. K., & Parker, S. K. (2010). Feeling good and performing well? Psychological engagement and positive behaviors at work. In S. Albrecht (Ed.), *Handbook of employee engagement: Perspectives, issues, research and practice* (pp. 385–398). Edward Elgar.
- Bindl, U. K., Parker, S. K., Totterdell, P., & Hagger-Johnson, G. (2012). Fuel of the self-starter: How mood relates to proactive goal regulation. *Journal of Applied Psychology*, 97(1), 134–150. <https://doi.org/10.1037/a0024368>
- Bindl, U. K., Unsworth, K. L., Gibson, C. B., & Stride, C. B. (2019). Job crafting revisited: Implications of an extended framework for active changes at work. *Journal of Applied Psychology*, 104(5), 605–628. <http://dx.doi.org/10.1037/apl0000362>
- Binnewies, C., & Gromer, M. (2012). Creativity and innovation at work: The role of work characteristics and personal initiative. *Psicothema*, 24(1), 100–105. <https://reunido.uniovi.es/index.php/PST/article/view/9110>
- Binnewies, C., Ohly, S., & Sonnentag, S. (2007). Taking personal initiative and communicating about ideas: What is important for the creative process and for idea creativity? *European Journal of Work and Organizational Psychology*, 16(4), 432–455. <https://doi.org/10.1080/13594320701514728>

- Binnewies, C., Sonnentag, S., & Mojza, E. J. (2009). Daily performance at work: Feeling recovered in the morning as a predictor of day-level job performance. *Journal of Organizational Behavior*, 30(1), 67–93. <https://doi.org/10.1002/job.541>
- Binnewies, C., & Wörlein, S. C. (2011). What makes a creative day? A diary study on the interplay between affect, job stressors, and job control. *Journal of Organizational Behavior*, 32(4), 589–607. <https://doi.org/10.1002/job.731>
- Biron, M., & van Veldhoven, M. (2016). When control becomes a liability rather than an asset: Comparing home and office days among part-time teleworkers. *Journal of Organizational Behavior*, 37(8), 1317–1337. <https://doi.org/10.1002/job.2106>
- Blanka, C. (2019). An individual-level perspective on intrapreneurship: A review and ways forward. *Review of Managerial Science*, 13(5), 919–961. <https://doi.org/10.1007/s11846-018-0277-0>
- Bledow, R., Rosing, K., & Frese, M. (2013). A dynamic perspective on affect and creativity. *Academy of Management Journal*, 56(2), 432–450. <https://doi.org/10.5465/amj.2010.0894>
- Boeker, W., Howard, M. D., Basu, S., & Sahaym, A. (2019). Interpersonal relationships, digital technologies, and innovation in entrepreneurial ventures. *Journal of Business Research*. Advance online publication. <https://doi.org/10.1016/j.jbusres.2019.09.003>
- Boomsma, A., & Hoogland, J. J. (2001). The robustness of LISREL modeling revisited. In R. Cudeck, S. du Toit, & D. Sorbom (Eds.), *Structural equation modeling: Present and future* (pp. 139–168). SSI Scientific Software.
- Bormann, K. C. (2017). Linking daily ethical leadership to followers' daily behaviour: The roles of daily work engagement and previous abusive supervision. *European Journal of Work and Organizational Psychology*, 26(4), 590–600. <https://doi.org/10.1080/1359432X.2017.1331217>

- Bosch, C., Sonnentag, S., & Pinck, A. S. (2018). What makes for a good break? A diary study on recovery experiences during lunch break. *Journal of Occupational and Organizational Psychology*, 91(1), 134–157. <https://doi.org/10.1111/joop.12195>
- Boyd, C. M., Bakker, A. B., Pignata, S., Winefield, A. H., Gillespie, N., & Stough, C. (2011). A longitudinal test of the job demands-resources model among Australian university academics. *Applied Psychology*, 60(1), 112–140. <https://doi.org/10.1111/j.1464-0597.2010.00429.x>
- Braukmann, J., Schmitt, A., Ďuranová, L., & Ohly, S. (2018). Identifying ICT-related affective events across life domains and examining their unique relationships with employee recovery. *Journal of Business and Psychology*, 33(4), 529–544. <https://doi.org/10.1007/s10869-017-9508-7>
- Breevaart, K., Bakker, A. B., Demerouti, E., & van den Heuvel, M. (2015). Leader-member exchange, work engagement, and job performance. *Journal of Managerial Psychology*, 30(7), 754–770. <https://doi.org/10.1108/JMP-03-2013-0088>
- Breevaart, K., & Zacher, H. (2019). Daily selection, optimization, and compensation strategy use and innovative performance: The role of job autonomy and time pressure. *Journal of Personnel Psychology*, 18(2), 71–83. <https://doi.org/10.1027/1866-5888/a000224>
- Brehm, J. W. (1999). The intensity of emotion. *Personality and Social Psychology Review*, 3(1), 2–22. https://doi.org/10.1207/s15327957pspr0301_1
- Briggs, C., & Makice, K. (2012). *Digital fluency: Building success in the digital age*. SocialLens.
- Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology*, 1(3), 185–216. <https://doi.org/10.1177/135910457000100301>
- Brooks, S. (2015). Does personal social media usage affect efficiency and well-being? *Computers in Human Behavior*, 46, 26–37. <https://doi.org/10.1016/j.chb.2014.12.053>

- Brough, P., Timms, C., Siu, O. L., Kalliath, T., O'Driscoll, M. P., Sit, C. H., Lo, D., & Lu, C.-Q. (2013). Validation of the job demands-resources model in cross-national samples: Cross-sectional and longitudinal predictions of psychological strain and work engagement. *Human Relations*, 66(10), 1311–1335. <https://doi.org/10.1177/0018726712472915>
- Brown, T. R. (1972). A comparison of judgmental policy equations obtained from human judges under natural and contrived conditions. *Mathematics Bioscience*, 15(3-4), 205–230. [https://doi.org/10.1016/0025-5564\(72\)90036-3](https://doi.org/10.1016/0025-5564(72)90036-3)
- Brundin, E., Patzelt, H., & Shepherd, D. A. (2008). Managers' emotional displays and employees' willingness to act entrepreneurially. *Journal of Business Venturing*, 23(2), 221–243. <https://doi.org/10.1016/j.jbusvent.2006.10.009>
- Byrne, B. M. (2010). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (2nd ed.). Taylor & Francis. <https://doi.org/10.4324/9780203805534>
- Byrne, J., Delmar, F., Fayolle, A., & Lamine, W. (2016). Training corporate entrepreneurs: An action learning approach. *Small Business Economics*, 47(2), 479–506. <https://doi.org/10.1007/s11187-016-9734-9>
- Cacioppo, J. T., Gardner, W. L., & Berntson, G. G. (1999). The affect system has parallel and integrative processing components: Form follows function. *Journal of Personality and Social Psychology*, 76(5), 839–855. <https://doi.org/10.1037/0022-3514.76.5.839>
- Carlson, D. S., Kacmar, K. M., Zivnuska, S., Ferguson, M., & Whitten, D. (2011). Work-family enrichment and job performance: A constructive replication of affective events theory. *Journal of Occupational Health Psychology*, 16(3), 297–312. <https://doi.org/10.1037/a0022880>
- Carlson, J. R., Carlson, D. S., Zivnuska, S., Harris, R. B., & Harris, K. J. (2017). Applying the job demands resources model to understand technology as a predictor of turnover

- intentions. *Computers in Human Behavior*, 77, 317–325. <https://doi.org/10.1016/j.chb.2017.09.009>
- Carver, C. S., & Scheier, M. F. (2002). Optimism. In C. R. Snyder & S. J. Lopez (Eds.), *Handbook of positive psychology* (pp. 231–243). Oxford Press.
- Carver, C. S., & White, T. L. (1994). Behavioral-inhibition, behavioral activation, and affective responses to impending reward and punishment. The BIS/BAS scales. *Journal of Personality and Social Psychology*, 67(2), 319–333. <https://doi.org/10.1037/0022-3514.67.2.319>
- Cavanaugh, G. F., & Fritzsche, D. J. (1985). Using vignettes in business ethics research. In L. E. Preston (Ed.), *Research in corporate social performance and policy* (Vol. 7, pp. 279–293). Jai Press.
- Černe, M., Jaklič, M., & Škerlavaj, M. (2013). Management innovation in focus: The role of knowledge exchange, organizational size, and IT system development and utilization. *European Management Review*, 10(3), 153–166. <https://doi.org/10.1111/emre.12013>
- Chandra, S., Shirish, A., & Srivastava, S. C. (2019). Does technostress inhibit employee innovation? Examining the linear and curvilinear influence of technostress creators. *Communications of the Association for Information Systems*, 44, 299–331. <https://doi.org/10.17705/1CAIS.04419>
- Chang, H. T., Hsu, H. M., Liou, J. W., & Tsai, C. T. (2013). Psychological contracts and innovative behavior: A moderated path analysis of work engagement and job resources. *Journal of Applied Social Psychology*, 43(10), 2120–2135. <https://doi.org/10.1111/jasp.12165>
- Chen, S., Westman, M., & Eden, D. (2009). Impact of enhanced resources on anticipatory stress and adjustment to new information technology: A field-experimental test of conservation

- of resources theory. *Journal of Occupational Health Psychology*, 14(3), 219–230.
<https://doi.org/10.1037/a0015282>
- Chen, Y., Wang, Y., Nevo, S., Benitez-Amado, J., & Kou, G. (2015). IT capabilities and product innovation performance: The roles of corporate entrepreneurship and competitive intensity. *Information & Management*, 52(6), 643–657. <https://doi.org/10.1016/j.im.2015.05.003>
- Cho, J., Ramgolam, D. I., Schaefer, K. M., & Sandlin, A. N. (2011). The rate and delay in overload: An investigation of communication overload and channel synchronicity on identification and job satisfaction. *Journal of Applied Communication Research*, 39(1), 38–54. <https://doi.org/10.1080/00909882.2010.536847>
- Chow, W., & Ng, M. (2016). Disintermediator or another intermediary? E-simulation platform for professional legal education at University of Hong Kong. *European Journal of Law and Technology*, 7(1), 1–21. <http://ejlt.org/index.php/ejlt/article/view/502>
- Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences*. (3rd ed.). Lawrence Erlbaum.
- Cole, D. A., & Preacher, K. J. (2014). Manifest variable path analysis: Potentially serious and misleading consequences due to uncorrected measurement error. *Psychological Methods*, 19(2), 300–315. <https://doi.org/10.1037/a0033805>
- Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, 19(2), 189–211. <https://doi.org/10.2307/249688>
- Cooksey, R. (1996). *Judgement analysis: Theory, methods, and applications*. Academic Press.
- Cooper, C. L., Dewe, P. J., & O’Driscoll, M. P. (2001). *Organizational stress*. Sage.
- Crant, J. M. (1996). The proactive personality scale as a predictor of entrepreneurial intentions. *Journal of Small Business Management*, 34(3), 42–49. <https://homepages.se.edu/>

cvonbergen/files/2013/01/Proactive_Personality-Scale-as-a-Predictor-of-Entrepreneurial-Intentions.pdf

Cropanzano, R., & Wright, T. A. (2001). When a happy worker is really a productive worker: A review and further refinement of the happy-productive worker thesis. *Consulting Psychology Journal: Practice and Research*, 53(3), 182–199. <https://doi.org/10.1037/1061-4087.53.3.182>

Crowston, K., & Myers, M. D. (2004). Information technology and the transformation of industries: Three research perspectives. *Journal of Strategic Information Systems*, 13(1), 5–28. <https://doi.org/10.1016/j.jsis.2004.02.001>

Davidson, E., & Vaast, E. (2010). Digital entrepreneurship and its sociomaterial enactment. In R. H. Sprague Jr. (Ed), *Proceedings of the 43rd Annual Hawaii International Conference on System Sciences* (pp. 2978–2987). Institute of Electrical and Electronics Engineers. <https://doi.org/10.1109/HICSS.2010.150>

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982–1003. <https://doi.org/10.1287/mnsc.35.8.982>

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, 22(14), 1111–1132. <https://doi.org/10.1111/j.1559-1816.1992.tb00945.x>

Dawson, J. F., & Richter, A. W. (2006). Probing three-way interactions in moderated multiple regression: Development and application of a slope difference test. *Journal of Applied Psychology*, 91(4), 917–926. <https://doi.org/10.1037/0021-9010.91.4.917>

- Day, A., Paquet, S., Scott, N., & Hambley, L. (2012). Perceived information and communication technology (ICT) demands on employee outcomes: The moderating effect of organizational ICT support. *Journal of Occupational Health Psychology, 17*(4), 473–491. <https://doi.org/10.1037/a0029837>
- Day, A., Scott, N., & Kelloway, E. K. (2010). Information and communication technology: Implications for job stress and employee well-being. In P. L. Perrewé & D. C. Ganster (Eds.), *New developments in theoretical and conceptual approaches to job stress* (Vol. 8, pp. 317–350). Emerald Group Publishing. [https://doi.org/10.1108/S1479-3555\(2010\)0000008011](https://doi.org/10.1108/S1479-3555(2010)0000008011)
- de Clercq, D., Dimov, D., & Belausteguigoitia, I. (2016). Perceptions of adverse work conditions and innovative behavior: The buffering roles of relational resources. *Entrepreneurship Theory and Practice, 40*(3), 515–542. <https://doi.org/10.1111/etap.12121>
- de Clercq, D., Sun, W., & Belausteguigoitia, I. (2018). When is job control most useful for idea championing? Role conflict and psychological contract violation effects. *Journal of Management & Organization*, Advance online publication. <https://doi.org/10.1017/jmo.2018.28>
- de Jong, J., & den Hartog, D. (2010). Measuring innovative work behaviour. *Creativity and Innovation Management, 19*(1), 23–36. <https://doi.org/10.1111/j.1467-8691.2010.00547.x>
- Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology, 86*(3), 499–512. <https://doi.org/10.1037/0021-9010.86.3.499>
- Demerouti, E., & Rispens, S. (2014). Improving the image of student-recruited samples: A commentary. *Journal of Occupational and Organizational Psychology, 87*(1), 34–41. <https://doi.org/10.1111/joop.12048>

- de Spiegelaere, S., van Gyes, G., de Witte, H., Niesen, W., & van Hootegeem, G. (2014). On the relation of job insecurity, job autonomy, innovative work behaviour and the mediating effect of work engagement. *Creativity and Innovation Management*, 23(3), 318–330. <https://doi.org/10.1111/caim.12079>
- de Villiers-Scheepers, M. J. (2012). Antecedents of strategic corporate entrepreneurship. *European Business Review*, 24(5), 400–424. <https://doi.org/10.1108/09555341211254508>
- Diaz, I., Chiaburu, D. S., Zimmerman, R. D., & Boswell, W. R. (2012). Communication technology: Pros and cons of constant connection to work. *Journal of Vocational Behavior*, 80(2), 500–508. <https://doi.org/10.1016/j.jvb.2011.08.007>
- Diebig, M., Bormann, K. C., & Rowold, J. (2016). A double-edged sword: Relationship between full-range leadership behaviors and followers' hair cortisol level. *The Leadership Quarterly*, 27(4), 684–696. <https://doi.org/10.1016/j.leaqua.2016.04.001>
- Dimov, D. (2007). Beyond the single-person, single-insight attribution in understanding entrepreneurial opportunities. *Entrepreneurship Theory and Practice*, 31(5), 713–731. <https://doi.org/10.1111/j.1540-6520.2007.00196.x>
- Dodgson, M., Gann, D. M., & Salter, A. J. (2002). The intensification of innovation. *International Journal of Innovation Management*, 6(1), 53–83. <https://doi.org/10.1142/S1363919602000495>
- Doll, W. J., & Deng, X. (2001). The collaborative use of information technology: End-user participation and systems success. *Information Resources Management Journal*, 14(2), 6–16. <https://doi.org/10.4018/irmj.2001040101>
- Doluc, H., Wagner, M., & Block, J. (2018). Sustainability and environmental behaviour in family firms: A longitudinal analysis of environment-related activities, innovation and

- performance. *Business Strategy and the Environment*, 27(1), 152–172. <https://doi.org/10.1002/bse.1998>
- Douglas, E. J., & Fitzsimmons, J. R. (2013). Intrapreneurial intentions versus entrepreneurial intentions: Distinct constructs with different antecedents. *Small Business Economics*, 41(1), 115–132. <https://doi.org/10.1007/s11187-012-9419-y>
- Douglas, S. P., & Craig, C. S. (2007). Collaborative and iterative translation: An alternative approach to back translation. *Journal of International Marketing*, 15(1), 30–43. <https://doi.org/10.1509/jimk.15.1.030>
- Drover, W., Wood, M. S., & Payne, G. T. (2014). The effects of perceived control on venture capitalist investment decisions: A configurational perspective. *Entrepreneurship Theory and Practice*, 38(4), 833–861. <https://doi.org/10.1111/etap.12012>
- Eddy, E. R., Stone, D. L., & Stone-Romero, E. F. (1999). The effects of information management policies on reactions to human resource information systems: An integration of privacy and procedural justice perspectives. *Personnel Psychology*, 52(2), 335–358. <https://doi.org/10.1111/j.1744-6570.1999.tb00164.x>
- Engelen, A., Engelen, M., & Bachmann, J.-T. (2015). *Corporate Entrepreneurship: Unternehmerisches Management in etablierten Unternehmen* [Corporate entrepreneurship: Entrepreneurial management in established corporations]. Springer Gabler. <https://doi.org/10.1007/978-3-658-00646-4>
- Epstein, S., Pacini, R., Denes-Raj, V., & Heier, H. (1996). Individual differences in intuitive-experiential and analytical-rational thinking styles. *Journal of Personality and Social Psychology*, 71(2), 390–405. <https://doi.org/10.1037/0022-3514.71.2.390>
- Evans, D. S., & Leighton, L. S. (1995). Retrospective bias in the displaced worker surveys. *Journal of Human Resources*, 30(2), 386–396. <https://doi.org/10.2307/146125>

- Evans, P. B., & Wurster, T. S. (1997). Strategy and the new economics of information. *Harvard Business Review*, 75(5), 65–82. <https://hbr.org/1997/09/strategy-and-the-new-economics-of-information>
- Ferris, D. L., Lian, H., Brown, D. J., & Morrison, R. (2015). Ostracism, self-esteem, and job performance: When do we self-verify and when do we self-enhance? *Academy of Management Journal*, 58(1), 279–297. <https://doi.org/10.5465/amj.2011.0347>
- Fieseler, C., & Fleck, M. (2013). The pursuit of empowerment through social media: Structural social capital dynamics in CSR-blogging. *Journal of Business Ethics*, 118(4), 759–775. <https://doi.org/10.1007/s10551-013-1959-9>
- Finney, S., & DiStefano, C. (2006). Nonnormal and categorical data in structural equation modeling. In G. R. Hancock & R. O. Mueller (Eds.), *Structural equation modeling: A second course* (pp. 269–314). Information Age.
- Fischhoff, B. (1988). Judgement and decision-making. In E. Sternberg & E. Smith (Eds.), *The psychology of human thought* (pp. 155–187). Cambridge University Press.
- Fisher, C. D., & To, M. L. (2012). Using experience sampling methodology in organizational behavior. *Journal of Organizational Behavior*, 33(7), 865–877. <https://doi.org/10.1002/job.1803>
- Fitzsimmons, J. R., & Douglas, E. J. (2011). Interaction between feasibility and desirability in the formation of entrepreneurial intentions. *Journal of Business Venturing*, 26(4), 431–440. <https://doi.org/10.1016/j.jbusvent.2010.01.001>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>

- Fredrickson, B. L. (1998). What good are positive emotions? *Review of General Psychology*, 2(3), 300–319. <https://doi.org/10.1037/1089-2680.2.3.300>
- Frese, M., Fay, D., Hilburger, T., Leng, K., & Tag, A. (1997). The concept of personal initiative: Operationalization, reliability and validity in two German samples. *Journal of Occupational and Organizational Psychology*, 70(2), 139–161. <https://doi.org/10.1111/j.2044-8325.1997.tb00639.x>
- Frese, M., Kring, W., Soose, A., & Zempel, J. (1996). Personal initiative at work: Differences between east and west Germany. *Academy of Management Journal*, 39(1), 37–63. <https://doi.org/10.5465/256630>
- Frijda, N. H. (1986). *The emotions*. Cambridge University Press.
- Fritz, C., & Sonnentag, S. (2009). Antecedents of day-level proactive behavior: A look at job stressors and positive affect during the workday. *Journal of Management*, 35(1), 94–111. <https://doi.org/10.1177/0149206307308911>
- Fuglseth, A. M., & Sørenbø, Ø. (2014). The effects of technostress within the context of employee use of ICT. *Computers in Human Behavior*, 40, 161–170. <https://doi.org/10.1016/j.chb.2014.07.040>
- Fusilier, M. R., & Hoyer, W. D. (1980). Variables affecting perceptions of invasion of privacy in a personnel selection situation. *Journal of Applied Psychology*, 65(5), 623–626. <https://doi.org/10.1037/0021-9010.65.5.623>
- Gabriel, A. S., Podsakoff, N. P., Beal, D. J., Scott, B. A., Sonnentag, S., Trougakos, J. P., & Butts, M. M. (2019). Experience sampling methods: A discussion of critical trends and considerations for scholarly advancement. *Organizational Research Methods*, 22(4), 969–1006. <https://doi.org/10.1177/1094428118802626>

- Galluch, P. S., Grover, V., & Thatcher, J. B. (2015). Interrupting the workplace: Examining stressors in an information technology context. *Journal of the Association for Information Systems*, 16(1), 1–47. <https://doi.org/10.17705/1jais.00387>
- Gao, W., Liu, Z., Guo, Q., & Li, X. (2018). The dark side of ubiquitous connectivity in smartphone-based SNS: An integrated model from information perspective. *Computers in Human Behavior*, 84, 185–193. <https://doi.org/10.1016/j.chb.2018.02.023>
- Gawke, J. C., Gorgievski, M. J., & Bakker, A. B. (2017). Employee intrapreneurship and work engagement: A latent change score approach. *Journal of Vocational Behavior*, 100, 88–100. <https://doi.org/10.1016/j.jvb.2017.03.002>
- Gawke, J. C., Gorgievski, M. J., & Bakker, A. B. (2018). Personal costs and benefits of employee intrapreneurship: Disentangling the employee intrapreneurship, well-being, and job performance relationship. *Journal of Occupational Health Psychology*, 23(4), 508–519. <https://doi.org/10.1037/ocp0000105>
- Geldhof, G. J., Preacher, K. J., & Zyphur, M. J. (2014). Reliability estimation in a multilevel confirmatory factor analysis framework. *Psychological Methods*, 19(1), 72–91. <https://doi.org/10.1037/a0032138>
- Gellman, R. (1996). Disintermediation and the internet. *Government Information Quarterly*, 13(1), 1–8. [https://doi.org/10.1016/S0740-624X\(96\)90002-7](https://doi.org/10.1016/S0740-624X(96)90002-7)
- George, J. M. (1991). State or trait: Effects of positive mood on prosocial behaviors at work. *Journal of Applied Psychology*, 76(2), 299–307. <https://doi.org/10.1037/0021-9010.76.2.299>
- George, J. M. (1995). Leader positive mood and group performance: The case of customer service. *Journal of Applied Social Psychology*, 25(9), 778–794. <https://doi.org/10.1111/j.1559-1816.1995.tb01775.x>

- George, J. M., & Brief, A. P. (1996). Motivational agendas in the work-place: The effects of feelings on focus of attention and work motivation. In B. M. Staw & L. L. Cummings (Eds.), *Research in organizational behavior* (Vol. 18, pp. 75–109). JAI. Press.
- George, J. M., & Zhou, J. (2007). Dual tuning in a supportive context: Joint contributions of positive mood, negative mood, and supervisory behaviors to employee creativity. *Academy of Management Journal*, 50(3), 605–622. <https://doi.org/10.5465/amj.2007.25525934>
- German Federal Ministry of Education and Research (2019). *Total innovation expenditure, by sector groups and employment size classes*. <http://www.datenportal.bmbf.de/portal/en/Table-1.8.8.html>
- German Federal Statistical Office (2020). *Working hours in 2018: Longest hours worked in agriculture and forestry, shortest in manufacturing*. https://www.destatis.de/DE/Presse/Pressemitteilungen/2020/03/PD20_071_133.html
- Gillam, C., & Oppenheim, C. (2006). Reviewing the impact of virtual teams in the information age. *Journal of Information Science*, 32(2), 160–175. <https://doi.org/10.1177/0165551506062328>
- Gilson, L. L., & Shalley, C. E. (2004). A little creativity goes a long way: An examination of teams' engagement in creative processes. *Journal of Management*, 30(4), 453–470. <https://doi.org/10.1016/j.jm.2003.07.001>
- Glaser, L., Stam, W., & Takeuchi, R. (2016). Managing the risks of proactivity: A multilevel study of initiative and performance in the middle management context. *Academy of Management Journal*, 59(4), 1339–1360. <https://doi.org/10.5465/amj.2014.0177>

- Globocnik, D., & Salomo, S. (2015). Do formal management practices impact the emergence of bootlegging behavior? *Journal of Product Innovation Management*, 32(4), 505–521.
<https://doi.org/10.1111/jpim.12215>
- Gorgievski, M. J., Moriano, J. A., & Bakker, A. B. (2014). Relating work engagement and workaholism to entrepreneurial performance. *Journal of Managerial Psychology*, 29(2), 106–121. <https://doi.org/10.1108/JMP-06-2012-0169>
- Gumusluoğlu, L., & Ilsev, A. (2009). Transformational leadership and organizational innovation: The roles of internal and external support for innovation. *Journal of Product Innovation Management*, 26(3), 264–277. <https://doi.org/10.1111/j.1540-5885.2009.00657.x>
- Gupta, V., MacMillan, I. C., & Surie, G. (2004). Entrepreneurial leadership: Developing and measuring a cross-cultural construct. *Journal of Business Venturing*, 19(2), 241–260.
[https://doi.org/10.1016/S0883-9026\(03\)00040-5](https://doi.org/10.1016/S0883-9026(03)00040-5)
- Gustavsson, M., & Ljungberg, J. (2018). Entrepreneurship in the digital society. In J. Pries-Heje, S. Ram, & M. Rosemann (Eds.), *Proceedings of the 39th International Conference on Information Systems* (Vol. 3, pp. 2416–2427). Association for Information Systems.
<https://aisel.aisnet.org/icis2018/innovation/Presentations/17/>
- Haarhaus, T., Geiger, J. M., & Liening, A. (2018). The influence of digitalization on emergent processes of entrepreneurial ecosystems: A complexity science perspective. In J. Pries-Heje, S. Ram, & M. Rosemann (Eds.), *Proceedings of the 39th International Conference on Information Systems* (Vol. 4, pp. 2598–2606). Association for Information Systems.
<https://aisel.aisnet.org/icis2018/innovation/Presentations/27/>
- Hakanen, J. J., Perhoniemi, R., & Toppinen-Tanner, S. (2008). Positive gain spirals at work: From job resources to work engagement, personal initiative and work-unit innovativeness. *Journal of Vocational Behavior*, 73(1), 78–91. <https://doi.org/10.1016/j.jvb.2008.01.003>

- Halbesleben, J. R., Neveu, J. P., Paustian-Underdahl, S. C., & Westman, M. (2014). Getting to the “COR”: Understanding the role of resources in conservation of resources theory. *Journal of Management*, 40(5), 1334–1364. <https://doi.org/10.1177/0149206314527130>
- Hammond, K. R., & Adelman, L. (1976). Science, values, and human judgment. *Science*, 194(4263), 389–396. <https://doi.org/10.1126/science.194.4263.389>
- Hammond, M. M., Neff, N. L., Farr, J. L., Schwall, A. R., & Zhao, X. (2011). Predictors of individual-level innovation at work: A meta-analysis. *Psychology of Aesthetics, Creativity, and the Arts*, 5(1), 90–105. <https://doi.org/10.1037/a0018556>
- Han, Y., Wang, M., & Dong, L. (2014). Role conflict and the buffering effect of proactive personality among middle managers. *Social Behavior and Personality*, 42(3), 473–486. <https://doi.org/10.2224/sbp.2014.42.3.473>
- Hanafizadeh, M. R., Saghaei, A., & Hanafizadeh, P. (2009). An index for cross-country analysis of ICT infrastructure and access. *Telecommunications Policy*, 33(7), 385–405. <https://doi.org/10.1016/j.telpol.2009.03.008>
- Hanohov, R., & Baldacchino, L. (2018). Opportunity recognition in sustainable entrepreneurship: An exploratory study. *International Journal of Entrepreneurial Behavior & Research*, 24(2), 333–358. <https://doi.org/10.1108/IJEBR-12-2015-0275>
- Hardt, J. V. (2011). *Innovationskompetenz: Entwicklung und Validierung eines neuen Konstrukts* [Innovation competence: Development and validation of a new construct; Doctoral dissertation, University of Siegen]. OPUS Siegen. <https://dspace.ub.uni-siegen.de/bitstream/ubsi/596/1/hardt.pdf>
- Harris, K. J., Harris, R. B., Carlson, J. R., & Carlson, D. S. (2015). Resource loss from technology overload and its impact on work-family conflict: Can leaders help? *Computers in Human Behavior*, 50, 411–417. <https://doi.org/10.1016/j.chb.2015.04.023>

- Hauswald, H., Hack, A., Kellermanns, F. W., & Patzelt, H. (2016). Attracting new talent to family firms: Who is attracted and under what conditions? *Entrepreneurship Theory and Practice*, 40(5), 963–989. <https://doi.org/10.1111/etap.12153>
- Havakhor, T., Soror, A. A., & Sabherwal, R. (2018). Diffusion of knowledge in social media networks: Effects of reputation mechanisms and distribution of knowledge roles. *Information Systems Journal*, 28(1), 104–141. <https://doi.org/10.1111/isj.12127>
- Hayton, J. C., George, G., & Zahra, S. A. (2002). National culture and entrepreneurship: A review of behavioral research. *Entrepreneurship Theory and Practice*, 26(4), 33–52. <https://doi.org/10.1177/104225870202600403>
- Heinlen, C., Hovick, S. R., Brock, G. N., Klammer, B. G., Toland, A. E., & Senter, L. (2019). Exploring genetic counselors' perceptions of usefulness and intentions to use refined risk models in clinical care based on the technology acceptance model (TAM). *Journal of Genetic Counseling*, 28(3), 664–672. <https://doi.org/10.1002/jgc4.1079>
- Hernandez, L., Alhemood, A., Genaidy, A. M., & Karwowski, W. (2002). Evaluation of different scales for measurement of perceived physical strain during performance of manual tasks. *International Journal of Occupational Safety and Ergonomics*, 8(4), 413–432. <https://doi.org/10.1080/10803548.2002.11076545>
- Hiltz, S. R., & Turoff, M. (1985). Structuring computer-mediated communication systems to avoid information overload. *Communications of the ACM*, 28(7), 680–689. <https://doi.org/10.1145/3894.3895>
- Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist*, 44(3), 513–524. <https://doi.org/10.1037/0003-066X.44.3.513>

- Hobfoll, S. E. (2001). The influence of culture, community, and the nested-self in the stress process: Advancing conservation of resources theory. *Applied Psychology*, 50(3), 337–421. <https://doi.org/10.1111/1464-0597.00062>
- Hobfoll, S. E., Halbesleben, J., Neveu, J. P., & Westman, M. (2018). Conservation of resources in the organizational context: The reality of resources and their consequences. *Annual Review of Organizational Psychology and Organizational Behavior*, 5, 103–128. <https://doi.org/10.1146/annurev-orgpsych-032117-104640>
- Hobfoll, S. E., Johnson, R. J., Ennis, N., & Jackson, A. P. (2003). Resource loss, resource gain, and emotional outcomes among inner city women. *Journal of Personality and Social Psychology*, 84(3), 632–643. <https://doi.org/10.1037/0022-3514.84.3.632>
- Hobfoll, S. E., & Shirom, A. (2001). Conservation of resources theory: Applications to stress and management in the workplace. In R. T. Golembiewski (Ed.), *Handbook of organizational behavior* (pp. 57–81). Marcel Dekker.
- Hockey, G. J. (1997). Compensatory control in the regulation of human performance under stress and high workload: A cognitive-energetical framework. *Biological Psychology*, 45(1–3), 73–93. [https://doi.org/10.1016/S0301-0511\(96\)05223-4](https://doi.org/10.1016/S0301-0511(96)05223-4)
- Hofeditz, M., Nienaber, A. M., Dysvik, A., & Schewe, G. (2017). “Want to” versus “have to”: Intrinsic and extrinsic motivators as predictors of compliance behavior intention. *Human Resource Management*, 56(1), 25–49. <https://doi.org/10.1002/hrm.21774>
- Holland, D. V., & Garrett, R. P. (2015). Entrepreneur start-up versus persistence decisions: A critical evaluation of expectancy and value. *International Small Business Journal*, 33(2), 194–215. <https://doi.org/10.1177/0266242613480375>
- Hollen, R. M., van den Bosch, F. A., & Volberda, H. W. (2013). The role of management innovation in enabling technological process innovation: An inter-organizational

- perspective. *European Management Review*, 10(1), 35–50. <https://doi.org/10.1111/emre.12003>
- Hornsby, J. S., Kuratko, D. F., Holt, D. T., & Wales, W. J. (2013). Assessing a measurement of organizational preparedness for corporate entrepreneurship. *Journal of Product Innovation Management*, 30(5), 937–955. <https://doi.org/10.1111/jpim.12038>
- Hornsby, J. S., Kuratko, D. F., Shepherd, D. A., & Bott, J. P. (2009). Managers' corporate entrepreneurial actions: Examining perception and position. *Journal of Business Venturing*, 24(3), 236–247. <https://doi.org/10.1016/j.jbusvent.2008.03.002>
- Hornsby, J. S., Kuratko, D. F., & Zahra, S. A. (2002). Middle managers' perception of the internal environment for corporate entrepreneurship: Assessing a measurement scale. *Journal of Business Venturing*, 17(3), 253–273. [https://doi.org/10.1016/S0883-9026\(00\)00059-8](https://doi.org/10.1016/S0883-9026(00)00059-8)
- Hornsby, J. S., Naffziger, D. W., Kuratko, D. F., & Montagno, R. V. (1993). An interactive model of the corporate entrepreneurship process. *Entrepreneurship Theory and Practice*, 17(2), 29–37. <https://doi.org/10.1177/104225879301700203>
- Hsu, D. K., Simmons, S. A., & Wieland, A. M. (2017). Designing entrepreneurship experiments: A review, typology, and research agenda. *Organizational Research Methods*, 20(3), 379–412. <https://doi.org/10.1177/1094428116685613>
- Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>
- Hung, S. Y. (2003). Expert versus novice use of the executive support systems: An empirical study. *Information & Management*, 40(3), 177–189. [https://doi.org/10.1016/S0378-7206\(02\)00003-4](https://doi.org/10.1016/S0378-7206(02)00003-4)

- Igbaria, M., Parasuraman, S., & Baroudi, J. J. (1996). A motivational model of microcomputer usage. *Journal of Management Information Systems*, 13(1), 127–143. <https://doi.org/10.1080/07421222.1996.11518115>
- Ireland, R. D., Hitt, M. A., & Sirmon, D. G. (2003). A model of strategic entrepreneurship. *Journal of Management*, 29(6), 963–989. https://doi.org/10.1016/S0149-2063_03_00086-2
- Ito, J. K., & Brotheridge, C. M. (2003). Resources, coping strategies, and emotional exhaustion: A conservation of resources perspective. *Journal of Vocational Behavior*, 63(3), 490–509. [https://doi.org/10.1016/S0001-8791\(02\)00033-7](https://doi.org/10.1016/S0001-8791(02)00033-7)
- Jackson, T. W., Dawson, R., & Wilson, D. (2003). Understanding email interaction increases organizational productivity. *Communications of the ACM*, 46(8), 80–84. <https://doi.org/10.1145/859670.859673>
- Jallat, F., & Capek, M. J. (2001). Disintermediation in question: New economy, new networks, new middlemen. *Business Horizons*, 44(2), 55–60. [https://doi.org/10.1016/S0007-6813\(01\)80023-9](https://doi.org/10.1016/S0007-6813(01)80023-9)
- Janssen, O. (2000). Job demands, perceptions of effort-reward fairness and innovative work behaviour. *Journal of Occupational and Organizational Psychology*, 73(3), 287–302. <https://doi.org/10.1348/096317900167038>
- Janssen, O. (2001). Fairness perceptions as a moderator in the curvilinear relationships between job demands, and job performance and job satisfaction. *Academy of Management Journal*, 44(5), 1039–1050. <https://doi.org/10.5465/3069447>
- Janssen, O. (2003). Innovative behaviour and job involvement at the price of conflict and less satisfactory relations with co-workers. *Journal of Occupational and Organizational Psychology*, 76(3), 347–364. <https://doi.org/10.1348/096317903769647210>

- Janssen, O. (2004). How fairness perceptions make innovative behavior more or less stressful. *Journal of Organizational Behavior*, 25(2), 201–215. <https://doi.org/10.1002/job.238>
- Jantan, H., Hamdan, A. R., & Othman, Z. A. (2010). Intelligent techniques for decision support system in human resource management. In G. Devlin (Ed.), *Decision support systems: Advances in* (pp. 261–276). InTech. <https://doi.org/10.5772/39401>
- Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586. <https://doi.org/10.1016/j.bushor.2018.03.007>
- Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of Consumer Research*, 30(2), 199–218. <https://doi.org/10.1086/376806>
- Jessri, M., Kosmidou, V., & Ahuja, M. K. (2020). Employees' decision to participate in corporate venturing: A conjoint experiment of financial and non-financial motivations. *Journal of Business Venturing Insights*, 13, Article e00161. <https://doi.org/10.1016/j.jbvi.2020.e00161>
- Johansson-Hiden, B., Wastlund, E., & Wallin, S. (2003). Reflecting on ICT and stress: Conceptual connections and a suggested application. In J. S. Petterson (Ed.), *HumanIT 2003* (pp. 35–57). Karlstad University Studies.
- Jones, E. E., & Nisbett, R. E. (1971). *The actor and the observer: Divergent perceptions of the causes of behavior*. General Learning Press.
- Junglas, I., Goel, L., Ives, B., & Harris, J. (2019). Innovation at work: The relative advantage of using consumer IT in the workplace. *Information Systems Journal*, 29(2), 317–339. <https://doi.org/10.1111/isj.12198>

- Kahn, R. L., & Byosiére, P. (1992). Stress in organizations. In M. D. Dunnette & L. M. Hough (Eds.), *Handbook of industrial and organizational psychology* (pp. 571–650). Consulting Psychologists Press.
- Kallinikos, J., Aaltonen, A., & Marton, A. (2013). The ambivalent ontology of digital artifacts. *MIS Quarterly*, 37(2), 357–370. <https://doi.org/10.25300/MISQ/2013/37.2.02>
- Kankanhalli, A., Ye, H., & Teo, H. H. (2015). Comparing potential and actual innovators: An empirical study of mobile data services innovation. *MIS Quarterly*, 39(3), 667–682. <https://doi.org/10.25300/MISQ/2015/39.3.07>
- Kanter, R. M. (1988). When a 1000 flowers bloom: Structural, collective, and social conditions for innovation in organization. In B. M. Staw & L. L. Cummings (Eds.), *Research in organizational behavior* (Vol. 10, pp. 169–211). JAI Press.
- Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons*, 53(1), 59–68. <https://doi.org/10.1016/j.bushor.2009.09.003>
- Karr-Wisniewski, P., & Lu, Y. (2010). When more is too much: Operationalizing technology overload and exploring its impact on knowledge worker productivity. *Computers in Human Behavior*, 26(5), 1061–1072. <https://doi.org/10.1016/j.chb.2010.03.008>
- Keller, J., Bohner, G., & Erb, H. P. (2000). Intuitive und heuristische Urteilsbildung – verschiedene Prozesse? Präsentation einer deutschen Fassung des „Rational-Experiential Inventory “ sowie neuer Selbstberichtskalen zur Heuristiknutzung [Intuitive and heuristic formation of judgement – different processes? Presentation of a German version of the "Rational-Experiential Inventory " and new self-report scales for the use of heuristics]. *Zeitschrift für Sozialpsychologie*, 31(2), 87–101. <https://doi.org/10.1024//0044-3514.31.2.87>

- Kim, S., & Christensen, A. L. (2017). The dark and bright sides of personal use of technology at work: A job demands – resources model. *Human Resource Development Review*, 16(4), 425–447. <https://doi.org/10.1177/1534484317725438>
- Kleinschmidt, S., Peters, C., & Leimester, J. M. (2016). ICT-enabled service innovation in human-centered service systems: A systematic literature review. In P. J. Agerfalk, N. Levina, & S. S. Kien (Eds.), *Proceedings of the 37th International Conference on Information Systems* (Vol. 7, pp. 5478–5495). Association for Information Systems. <http://dx.doi.org/10.2139/ssrn.3159136>
- Korsgaard, M. A., & Roberson, L. (1995). Procedural justice in performance evaluation: The role of instrumental and non-instrumental voice in performance appraisal discussions. *Journal of Management*, 21(4), 657–669. <https://doi.org/10.1177/014920639502100404>
- Korzynski, P., Paniagua, J., & Rodriguez-Montemayor, E. (2019). Employee creativity in a digital era: The mediating role of social media. *Management Decision*, 58(6), 1100–1117. <https://doi.org/10.1108/MD-05-2018-0586>
- Krueger, N. F., Jr., & Dickson, P. R. (1993). Perceived self-efficacy and perceptions of opportunity and threat. *Psychological Reports*, 72(3), 1235–1240. <https://doi.org/10.2466/pr0.1993.72.3c.1235>
- Krueger, N. F., Jr., & Dickson, P. R. (1994). How believing in ourselves increases risk taking: Perceived self-efficacy and opportunity recognition. *Decision Sciences*, 25(3), 385–400. <https://doi.org/10.1111/j.1540-5915.1994.tb00810.x>
- Krueger, N. F., Jr., Reilly, M. D., & Carsrud, A. L. (2000). Competing models of entrepreneurial intentions. *Journal of Business Venturing*, 15(5–6), 411–432. [https://doi.org/10.1016/S0883-9026\(98\)00033-0](https://doi.org/10.1016/S0883-9026(98)00033-0)

- Kuratko, D. F., Hornsby, J. S., & Hayton, J. (2015). Corporate entrepreneurship: The innovative challenge for a new global economic reality. *Small Business Economics*, 45(2), 245–253. <https://doi.org/10.1007/s11187-015-9630-8>
- Kuratko, D. F., Ireland, R. D., Covin, J. G., & Hornsby, J. S. (2005). A model of middle-level managers' entrepreneurial behavior. *Entrepreneurship Theory and Practice*, 29(6), 699–716. <https://doi.org/10.1111/j.1540-6520.2005.00104.x>
- Kuratko, D. F., Morris, M. H., & Schindehutte, M. (2015). Understanding the dynamics of entrepreneurship through framework approaches. *Small Business Economics*, 45(1), 1–13. <https://doi.org/10.1007/s11187-015-9627-3>
- Kwanya, T., Stilwell, C., & Underwood, P. (2015). Apomediated marketplace: Effective ba for knowledge sharing and learning among local civil society organizations in developing countries. *Information Development*, 31(5), 461–472. <https://doi.org/10.1177/0266666914521827>
- Lam, H. K., Yeung, A. C., & Cheng, T. E. (2016). The impact of firms' social media initiatives on operational efficiency and innovativeness. *Journal of Operations Management*, 47–48(1), 28–43. <https://doi.org/10.1016/j.jom.2016.06.001>
- Larjovuori, R. L., Bordi, L., Mäkinen, J. P., & Heikkilä-Tammi, K. (2016). The role of leadership and employee well-being in organizational digitalization. In T. Russo-Spena & C. Mele (Eds.), *What's ahead in service research: New perspectives for business and society* (pp. 1141–1154). European Association for Research on Services. <https://www.reser.net/wp-content/uploads/2016/08/2016-Reser-Proceedings.pdf>
- Lee, C., Lee, C. C., & Kim, S. (2016). Understanding information security stress: Focusing on the type of information security compliance activity. *Computers & Security*, 59, 60–70. <https://doi.org/10.1016/j.cose.2016.02.004>

- Lee, S.-H., Magjuka, R., Liu, X., & Bonk, C. J. (2006). Interactive technologies for effective collaborative learning. *International Journal of Instructional Technology and Distance Learning*, 3(6), 17–32. http://www.itdl.org/Journal/Jun_06/article02.htm
- Lee, S. H., & Wong, P. K. (2004). An exploratory study of technopreneurial intentions: A career anchor perspective. *Journal of Business Venturing*, 19(1), 7–28. [https://doi.org/10.1016/S0883-9026\(02\)00112-X](https://doi.org/10.1016/S0883-9026(02)00112-X)
- Lei, C. F., & Ngai, E. W. T. (2014). The double-edged nature of technostress on work performance: A research model and research agenda. In M. D. Myers & D. W. Straub (Eds.), *Proceedings of the 35th International Conference on Information Systems* (Vol., 3, pp. 1790–1807). Association for Information Systems. <https://aisel.aisnet.org/icis2014/proceedings/HumanBehavior/41/>
- Leonardi, P. M. (2014). Social media, knowledge sharing, and innovation: Toward a theory of communication visibility. *Information Systems Research*, 25(4), 796–816. <https://doi.org/10.1287/isre.2014.0536>
- Leonardi, P. M., Huysman, M., & Steinfield, C. (2013). Enterprise social media: Definition, history, and prospects for the study of social technologies in organizations. *Journal of Computer-Mediated Communication*, 19(1), 1–19. <https://doi.org/10.1111/jcc4.12029>
- Li, L., Su, F., Zhang, W., & Mao, J. (2018). Digital transformation by SME entrepreneurs: A capability perspective. *Information Systems Journal*, 28(6), 1129–1157. <https://doi.org/10.1111/isj.12153>
- Lian, H., Ferris, D. L., & Brown, D. J. (2012). Does taking the good with the bad make things worse? How abusive supervision and leader–member exchange interact to impact need satisfaction and organizational deviance. *Organizational Behavior and Human Decision Processes*, 117(1), 41–52. <https://doi.org/10.1016/j.obhdp.2011.10.003>

- Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology*, 86(1), 114–121. <https://doi.org/10.1037/0021-9010.86.1.114>
- Liu, S. H., Liao, H. L., & Pratt, J. A. (2009). Impact of media richness and flow on e-learning technology acceptance. *Computers & Education*, 52(3), 599–607. <https://doi.org/10.1016/j.compedu.2008.11.002>
- Liu, Y., & Li, H. (2011). Exploring the impact of use context on mobile hedonic services adoption: An empirical study on mobile gaming in China. *Computers in Human Behavior*, 27(2), 890–898. <https://doi.org/10.1016/j.chb.2010.11.014>
- Louviere, J. J. (1988). *Analyzing decision-making: Metric conjoint analysis*. Sage. <https://dx.doi.org/10.4135/9781412983365>
- Lyytinen, K., Yoo, Y., & Boland, R. J., Jr. (2016). Digital product innovation within four classes of innovation networks. *Information Systems Journal*, 26(1), 47–75. <https://doi.org/10.1111/isj.12093>
- Madrid, H. P., & Patterson, M. G. (2020). How and for whom time control matter for innovation? The Role of positive affect and problem-solving demands. *Applied Psychology*, 69(1), 93–119. <https://doi.org/10.1111/apps.12194>
- Madrid, H. P., Patterson, M. G., Birdi, K. S., Leiva, P. I., & Kausel, E. E. (2014). The role of weekly high-activated positive mood, context, and personality in innovative work behavior: A multilevel and interactional model. *Journal of Organizational Behavior*, 35(2), 234–256. <https://doi.org/10.1002/job.1867>
- Madrid, H. P., Patterson, M. G., & Leiva, P. I. (2015). Negative core affect and employee silence: How differences in activation, cognitive rumination, and problem-solving demands

- matter. *Journal of Applied Psychology*, 100(6), 1887–1898. <https://doi.org/10.1037/a0039380>
- Maggiori, C., Johnston, C. S., Krings, F., Massoudi, K., & Rossier, J. (2013). The role of career adaptability and work conditions on general and professional well-being. *Journal of Vocational Behavior*, 83(3), 437–449. <https://doi.org/10.1016/j.jvb.2013.07.001>
- Mahdjour, S., & Fischer, S. (2014). International corporate entrepreneurship with born global spin-along venture: A cross-case analysis of Telekom innovation laboratories' venture portfolio. *International Journal of Innovation Management*, 18(3), 1–18. <https://doi.org/10.1142/S1363919614400076>
- Maier, C., Laumer, S., & Eckhardt, A. (2015). Information technology as daily stressor: Pinning down the causes of burnout. *Journal of Business Economics*, 85(4), 349–387. <https://doi.org/10.1007/s11573-014-0759-8>
- Majchrzak, A., & Markus, M. (2013). Technology affordances and constraints theory (of MIS). In E. Kessler (Ed.), *Encyclopedia of management theory* (pp. 832–836). Sage.
- Mäkinen, J. P., Ahola, S., & Joensuu, J. (2019). How are technology-related workplace resources associated with techno-work engagement among a group of Finnish teachers? *Seminar.net*, 15(1), 1–21. <https://journals.hioa.no/index.php/seminar/article/view/2919>
- Mäkinen, J. P., Ahola, S., & Joensuu, J. (2020). A novel construct to measure employees' technology-related experiences of well-being: Empirical validation of the Techno-Work Engagement Scale (TechnoWES). *Scandinavian Journal of Work and Organizational Psychology*, 5(1), Article 4. <http://doi.org/10.16993/sjwop.79>
- Malsbender, A., Hoffmann, S., & Becker, J. (2014). Aligning capabilities and social media affordances for open innovation in governments. *Australasian Journal of Information Systems*, 18(3), 317–330. <https://doi.org/10.3127/ajis.v18i3.1100>

- Masten, A. S. (2001). Ordinary magic: Resilience processes in development. *American Psychologist*, 56(3), 227–238. <https://doi.org/10.1037/0003-066X.56.3.227>
- McGrath, R. G. (1999). Falling forward: Real options reasoning and entrepreneurial failure. *Academy of Management Review*, 24(1), 13–30. <https://doi.org/10.5465/amr.1999.1580438>
- McGrath, R. G., & MacMillan, I. C. (2000). *The entrepreneurial mindset*. Harvard Business School Press.
- Meroño-Cerdán, A. L., Soto-Acosta, P., & López-Nicolás, C. (2008). How do collaborative technologies affect innovation in SMEs? *International Journal of e-Collaboration*, 4(4), 33–50. <https://doi.org/10.4018/jec.2008100103>
- Miller, D. (1983). The correlates of entrepreneurship in three types of firms. *Management Science*, 29(7), 770–791. <https://doi.org/10.1287/mnsc.29.7.770>
- Minbashian, A., Beckmann, N., & Wood, R. E. (2018). Emotional intelligence and individual differences in affective processes underlying task-contingent conscientiousness. *Journal of Organizational Behavior*, 39(9), 1182–1196. <https://doi.org/10.1002/job.2233>
- Monsen, E., Patzelt, H., & Saxton, T. (2010). Beyond simple utility: Incentive design and trade-offs for corporate employee-entrepreneurs. *Entrepreneurship Theory and Practice*, 34(1), 105–130. <https://doi.org/10.1111/j.1540-6520.2009.00314.x>
- Montani, F., Dagenais-Desmarais, V., Giorgi, G., & Grégoire, S. (2018). A conservation of resources perspective on negative affect and innovative work behaviour: The role of affect activation and mindfulness. *Journal of Business and Psychology*, 33(1), 123–139. <https://doi.org/10.1007/s10869-016-9480-7>

- Montoya, A. K., & Hayes, A. F. (2017). Two-condition within-participant statistical mediation analysis: A path-analytic framework. *Psychological Methods*, 22(1), 6–27. <https://doi.org/10.1037/met0000086>
- Moon, H., Kamdar, D., Mayer, D. M., & Takeuchi, R. (2008). Me or we? The role of personality and justice as other-centered antecedents to innovative citizenship behaviors within organizations. *Journal of Applied Psychology*, 93(1), 84–94. <https://doi.org/10.1037/0021-9010.93.1.84>
- Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, 2(3), 192–222. <https://doi.org/10.1287/isre.2.3.192>
- Moore, J. E. (2000). One road to turnover: An examination of work exhaustion in technology professionals. *MIS Quarterly*, 24(1), 141–168. <https://doi.org/10.2307/3250982>
- Moorman, R. H., Niehoff, B. P., & Organ, D. W. (1993). Treating employees fairly and organizational citizenship behavior: Sorting the effects of job satisfaction, organizational commitment, and procedural justice. *Employee Responsibilities and Rights Journal*, 6(3), 209–225. <https://doi.org/10.1007/BF01419445>
- Moreno, M., Schnabel, R., Lancia, G., & Woodruff, E. (2020). Between text and platforms: A case study on the real-time emotions & psychophysiological indicators of video gaming and academic engagement. *Education and Information Technologies*, 25(3), 2073–2099. <https://doi.org/10.1007/s10639-019-10031-3>
- Morgan, K., Morgan, M., & Hall, J. (2000). Psychological developments in high technology teaching and learning environments. *British Journal of Educational Technology*, 31(1), 71–79. <https://doi.org/10.1111/1467-8535.00136>

- Morris, M. H., Kuratko, D. F., & Covin, J. G. (2011). *Corporate entrepreneurship & innovation*. Cengage South-Western Publishers.
- Morris, M. H., Webb, J. W., & Franklin, R. J. (2011). Understanding the manifestation of entrepreneurial orientation in the nonprofit context. *Entrepreneurship Theory and Practice*, 35(5), 947–971. <https://doi.org/10.1111/j.1540-6520.2011.00453.x>
- Mossholder, K. W., Bennett, N., Kemery, E. R., & Wesolowski, M. A. (1998). Relationships between bases of power and work reactions: The mediational role of procedural justice. *Journal of Management*, 24(4), 533–552. <https://doi.org/10.1177/014920639802400404>
- Müller, T., & Niessen, C. (2019). Self-leadership in the context of part-time teleworking. *Journal of Organizational Behavior*, 40(8), 883–898. <https://doi.org/10.1002/job.2371>
- Murnieks, C. Y., Cardon, M. S., Sudek, R., White, T. D., & Brooks, W. T. (2016). Drawn to the fire: The role of passion, tenacity and inspirational leadership in angel investing. *Journal of Business Venturing*, 31(4), 468–484. <https://doi.org/10.1016/j.jbusvent.2016.05.002>
- Muthén, B. O., & Asparouhov, T. (2015). Causal effects in mediation modeling: An introduction with applications to latent variables. *Structural Equation Modeling: A Multidisciplinary Journal*, 22(1), 12–23. <https://doi.org/10.1080/10705511.2014.935843>
- Muthén, L. K., & Muthén, B. O. (2017). *Mplus user's guide* (8th ed.). Muthén & Muthén.
- Nambisan, S. (2013). Information technology and product/service innovation: A brief assessment and some suggestions for future research. *Journal of the Association for Information Systems*, 14(4), 215–226. <https://doi.org/10.17705/1jais.00327>
- Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice*, 41(6), 1029–1055. <https://doi.org/10.1111/etap.12254>

- Nambisan, S., & Baron, R. A. (2019). On the costs of digital entrepreneurship: Role conflict, stress, and venture performance in digital platform-based ecosystems. *Journal of Business Research*. Advance online publication. <https://doi.org/10.1016/j.jbusres.2019.06.037>
- 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>
- Nambisan, S., Siegel, D., & Kenney, M. (2018). On open innovation, platforms, and entrepreneurship. *Strategic Entrepreneurship Journal*, 12(3), 354–368. <https://doi.org/10.1002/sej.1300>
- Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, 48(8), Article 103773. <https://doi.org/10.1016/j.respol.2019.03.018>
- Narayanan, L., Menon, S., & Spector, P. (1999). Stress in the workplace: A comparison of gender and occupations. *Journal of Organizational Behavior*, 20(1), 63–74. [https://doi.org/10.1002/\(SICI\)1099-1379\(199901\)20:1<63::AID-JOB873>3.0.CO;2-J](https://doi.org/10.1002/(SICI)1099-1379(199901)20:1<63::AID-JOB873>3.0.CO;2-J)
- Neessen, P. C., Caniëls, M. C., Vos, B., & de Jong, J. P. (2019). The intrapreneurial employee: Toward an integrated model of intrapreneurship and research agenda. *International Entrepreneurship and Management Journal*, 15(2), 545–571. <https://doi.org/10.1007/s11365-018-0552-1>
- Newman, A., Herman, H. M., Schwarz, G., & Nielsen, I. (2018). The effects of employees' creative self-efficacy on innovative behavior: The role of entrepreneurial leadership. *Journal of Business Research*, 89, 1–9. <https://doi.org/10.1016/j.jbusres.2018.04.001>
- Newton, T. J., & Keenan, A. (1990). The moderating effect of the Type A behavior pattern and locus of control upon the relationship between change in job demands and change in

psychological strain. *Human Relations*, 43(12), 1229–1255. <https://doi.org/10.1177/001872679004301204>

Ng, T. W., & Feldman, D. C. (2012). Employee voice behavior: A meta-analytic test of the conservation of resources framework. *Journal of Organizational Behavior*, 33(2), 216–234. <https://doi.org/10.1002/job.754>

Ng, T. W., & Feldman, D. C. (2013). Age and innovation-related behavior: The joint moderating effects of supervisor undermining and proactive personality. *Journal of Organizational Behavior*, 34(5), 583–606. <https://doi.org/10.1002/job.1802>

Niehoff, B. P., & Moorman, R. H. (1993). Justice as a mediator of the relationship between methods of monitoring and organizational citizenship behavior. *Academy of Management Journal*, 36(3), 527–556. <https://doi.org/10.5465/256591>

Niessen, C., Sonnentag, S., & Sach, F. (2012). Thriving at work – A diary study. *Journal of Organizational Behavior*, 33(4), 468–487. <https://doi.org/10.1002/job.763>

Nöhammer, E., & Stichlberger, S. (2019). Digitalization, innovative work behavior and extended availability. *Journal of Business Economics*, 89(8–9), 1191–1214. <https://doi.org/10.1007/s11573-019-00953-2>

Ocampo, A. C. G., & Reyes, M. L. (2016). Resources for a positive perception of work among poor working youth. *Journal of Workplace Learning*, 28(6), 392–404. <https://doi.org/10.1108/JWL-10-2015-0075>

Ohly, S., Sonnentag, S., Niessen, C., & Zapf, D. (2010). Diary studies in organizational research. *Journal of Personnel Psychology*, 9(2), 79–93. <https://doi.org/10.1027/1866-5888/a000009>

- Ojala, A. (2016). Business models and opportunity creation: How IT entrepreneurs create and develop business models under uncertainty. *Information Systems Journal*, 26(5), 451–476. <https://doi.org/10.1111/isj.12078>
- Ong, C. S., & Lai, J. Y. (2006). Gender differences in perceptions and relationships among dominants of e-learning acceptance. *Computers in Human Behavior*, 22(5), 816–829. <https://doi.org/10.1016/j.chb.2004.03.006>
- Organ, D. W. (1988). *Organizational citizenship behavior: The good soldier syndrome*. Lexington Books.
- Organ, D. W., & Konovsky, M. (1989). Cognitive versus affective determinants of organizational citizenship behavior. *Journal of Applied Psychology*, 74(1), 157–164. <https://doi.org/10.1037/0021-9010.74.1.157>
- Orth, M., & Volmer, J. (2017). Daily within-person effects of job autonomy and work engagement on innovative behaviour: The cross-level moderating role of creative self-efficacy. *European Journal of Work and Organizational Psychology*, 26(4), 601–612. <https://doi.org/10.1080/1359432X.2017.1332042>
- Oulasvirta, A., & Sumari, L. (2007). Mobile kits and laptop trays: Managing multiple devices in mobile information work. In B. Begole, S. Payne, E. Churchill, R. St. Amant, D. Gilmore, & M. B. Rosson (Eds.), *CHI '07: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Vol. 2, pp. 1127–1136). Association for Computing Machinery. <https://doi.org/10.1145/1240624.1240795>
- Ouweneel, E., Le Blanc, P. M., & Schaufeli, W. B. (2012). Don't leave your heart at home: Gain cycles of positive emotions, resources, and engagement at work. *Career Development International*, 17(6), 537–556. <https://doi.org/10.1108/13620431211280123>

- Ozgen, E., & Baron, R. A. (2007). Social sources of information in opportunity recognition: Effects of mentors, industry networks, and professional forums. *Journal of Business Venturing*, 22(2), 174–192. <https://doi.org/10.1016/j.jbusvent.2005.12.001>
- Park, Y., Liu, Y., & Headrick, L. (2020). When work is wanted after hours: Testing weekly stress of information communication technology demands using boundary theory. *Journal of Organizational Behavior*, 41(6), 518–534. <https://doi.org/10.1002/job.2461>
- Parker, S. K., Bindl, U. K., & Strauss, K. (2010). Making things happen: A model of proactive motivation. *Journal of Management*, 36(4), 827–856. <https://doi.org/10.1177/0149206310363732>
- Parker, S. K., Williams, H. M., & Turner, N. (2006). Modeling the antecedents of proactive behavior at work. *Journal of Applied Psychology*, 91(3), 636–652. <https://doi.org/10.1037/0021-9010.91.3.636>
- Parthiban, R., Qureshi, I., Bandyopadhyay, S., & Jaikumar, S. (2021). Digitally mediated value creation for non-commodity base of the pyramid producers. *International Journal of Information Management*, 56, Article 102256. <https://doi.org/10.1016/j.ijinfomgt.2020.102256>
- Peterman, N. E., & Kennedy, J. (2003). Enterprise education: Influencing students' perceptions of entrepreneurship. *Entrepreneurship Theory and Practice*, 28(2), 129–144. <https://doi.org/10.1046/j.1540-6520.2003.00035.x>
- Petrou, P., & Bakker, A. B. (2016). Crafting one's leisure time in response to high job strain. *Human Relations*, 69(2), 507–529. <https://doi.org/10.1177/0018726715590453>
- Pieterse, A. N., van Knippenberg, D., Schippers, M., & Stam, D. (2010). Transformational and transactional leadership and innovative behavior: The moderating role of psychological

- empowerment. *Journal of Organizational Behavior*, 31(4), 609–623. <https://doi.org/10.1002/job.650>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Prahalad, C. K., & Ramaswamy, V. (2003). The new frontier of experience innovation. *MIT Sloan Management Review*, 44(4), 12–18. <https://sloanreview.mit.edu/article/the-new-frontier-of-experience-innovation/>
- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, 40(3), 879–891. <https://doi.org/10.3758/BRM.40.3.879>
- Preacher, K. J., Zyphur, M. J., & Zhang, Z. (2010). A general multilevel SEM framework for assessing multilevel mediation. *Psychological Methods*, 15(3), 209–233. <https://doi.org/10.1037/a0020141>
- Pundt, A., & Venz, L. (2017). Personal need for structure as a boundary condition for humor in leadership. *Journal of Organizational Behavior*, 38(1), 87–107. <https://doi.org/10.1002/job.2112>
- Qualman, E. (2010). *Socialnomics: How social media transforms the way we live and do business*. Wiley.
- Raghuram, S., Hill, N. S., Gibbs, J. L., & Maruping, L. M. (2019). Virtual work: Bridging research clusters. *Academy of Management Annals*, 13(1), 308–341. <https://doi.org/10.5465/annals.2017.0020>

- Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information Systems Research*, 19(4), 417–433. <https://doi.org/10.1287/isre.1070.0165>
- Remneland-Wikhamn, B., Ljungberg, J. A. N., Bergquist, M., & Kuschel, J. (2011). Open innovation, generativity and the supplier as peer: The case of iPhone and Android. *International Journal of Innovation Management*, 15(1), 205–230. <https://doi.org/10.1142/S1363919611003131>
- Rhee, H., & Kim, S. (2016). Effects of breaks on regaining vitality at work: An empirical comparison of ‘conventional’ and ‘smart phone’ breaks. *Computers in Human Behavior*, 57, 160–167. <https://doi.org/10.1016/j.chb.2015.11.056>
- Riaz, S., Xu, Y., & Hussain, S. (2018). Understanding employee innovative behavior and thriving at work: A Chinese perspective. *Administrative Sciences*, 8(3), 1–14. <https://doi.org/10.3390/admsci8030046>
- Rigtering, J. C., Weitzel, G. U., & Muehlfeld, K. K. (2019). Increasing quantity without compromising quality: How managerial framing affects intrapreneurship. *Journal of Business Venturing*, 34(2), 224–241. <https://doi.org/10.1016/j.jbusvent.2018.11.002>
- Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6), 1161–1178. <https://doi.org/10.1037/h0077714>
- Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological Review*, 110(1), 145–172. <https://doi.org/10.1037/0033-295X.110.1.145>
- Sánchez-Franco, M. J., Villarejo-Ramos, Á. F., Peral-Peral, B., Buitrago-Esquinas, E. M., & Roldán, J. L. (2013). Users’ perception of visual design and the usefulness of a web-based

- educational tool. *Procedia – Social and Behavioral Sciences*, 9, 1916–1921. <https://doi.org/10.1016/j.sbspro.2013.10.140>
- Sardeshmukh, S. R., & Corbett, A. C. (2011). The duality of internal and external development of successors: Opportunity recognition in family firms. *Family Business Review*, 24(2), 111–125. <https://doi.org/10.1177/0894486510391783>
- Sarma, V. V. S. (1994). Decision making in complex systems. *Systems Practice*, 7(4), 399–407. <https://doi.org/10.1007/BF02169361>
- Satorra, A., & Bentler, P. M. (2001). A scaled difference chi-square test statistic for moment structure analysis. *Psychometrika*, 66(4), 507–514. <https://doi.org/10.1007/BF02296192>
- Schaufeli, W. B., & Bakker, A. B. (2004). Job demands, job resources, and their relationship with burnout and engagement: A multi-sample study. *Journal of Organizational Behavior*, 25(3), 293–315. <https://doi.org/10.1002/job.248>
- Schaufeli, W. B., & Bakker, A. B. (2010). Defining and measuring work engagement: Bringing clarity to the concept. In A. B. Bakker & M. P. Leiter (Eds.), *Work engagement: A handbook of essential theory and research* (pp. 10–24). Psychology Press.
- Schaufeli, W. B., Salanova, M., González-Romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, 3(1), 71–92. <https://doi.org/10.1023/A:1015630930326>
- Schindler, J., Schindler, S., & Pfattheicher, S. (2020). The role of intuition in vaccination attitudes. *Journal of Health Psychology*. Advance online publication. <https://doi.org/10.1177/1359105320925160>
- Schmitt, A., den Hartog, D. N., & Belschak, F. D. (2016). Transformational leadership and proactive work behaviour: A moderated mediation model including work engagement and

job strain. *Journal of Occupational and Organizational Psychology*, 89(3), 588–610.

<https://doi.org/10.1111/joop.12143>

Schneckenberg, D., Truong, Y., & Mazloomi, H. (2015). Microfoundations of innovative capabilities: The leverage of collaborative technologies on organizational learning and knowledge management in a multinational corporation. *Technological Forecasting and Social Change*, 100, 356–368. <https://doi.org/10.1016/j.techfore.2015.08.008>

Schultze, U., & Vandenbosch, B. (1998). Information overload in a groupware environment: Now you see it, now you don't. *Journal of Organizational Computing and Electronic Commerce*, 8(2), 127–148. https://doi.org/10.1207/s15327744joce0802_3

Schumacker, R. E., & Lomax, R. G. (2010). *A beginner's guide to structural equation modeling* (3rd ed.). Routledge. <https://doi.org/10.4324/9780203851319>

Scott, S. G., & Bruce, R. A. (1994). Determinants of innovative behavior: A path model of individual innovation in the workplace. *Academy of Management Journal*, 37(3), 580–607. <https://doi.org/10.5465/256701>

Seo, M. G., Bartunek, J. M., & Barrett, L. F. (2010). The role of affective experience in work motivation: Test of a conceptual model. *Journal of Organizational Behavior*, 31(7), 951–968. <https://doi.org/10.1002/job.655>

Serin, H. (2018). The use of extrinsic and intrinsic motivations to enhance student achievement in educational settings. *International Journal of Social Sciences & Educational Studies*, 5(1), 191–194. <https://doi.org/10.23918/ijsses.v5i1p191>

Shane, S., Locke, E. A., & Collins, C. J. (2003). Entrepreneurial motivation. *Human Resource Management Review*, 13(2), 257–279. [https://doi.org/10.1016/S1053-4822\(03\)00017-2](https://doi.org/10.1016/S1053-4822(03)00017-2)

- Sharma, P., & Chrisman, J. J. (1999). Toward a reconciliation of the definitional issues in the field of corporate entrepreneurship. *Entrepreneurship Theory and Practice*, 23(3), 11–28. <https://doi.org/10.1177/104225879902300302>
- Shen, K. N., Lindsay, V., & Xu, Y. C. (2018). Digital entrepreneurship. *Information Systems Journal*, 28(6), 1125–1128. <https://doi.org/10.1111/isj.12219>
- Shepherd, D. A. (1999). Venture capitalists' assessment of new venture survival. *Management Science*, 45(5), 621–632. <https://doi.org/10.1287/mnsc.45.5.621>
- Shepherd, D. A., Haynie, J. M., & Patzelt, H. (2013). Project failures arising from corporate entrepreneurship: Impact of multiple project failures on employees' accumulated emotions, learning, and motivation. *Journal of Product Innovation Management*, 30(5), 880–895. <https://doi.org/10.1111/jpim.12035>
- Shepherd, D. A., & Patzelt, H. (2017). *Trailblazing in entrepreneurship: Creating new paths for understanding the field*. Palgrave MacMillan. <https://doi.org/10.1007/978-3-319-48701-4>
- Shepherd, D. A., & Zacharakis, A. (1997). Conjoint analysis: A window of opportunity for entrepreneurship research. In J. Katz (Ed.), *Advances in entrepreneurship, firm emergence and growth* (Vol. 3, pp. 203–248). JAI Press.
- Shepherd, D. A., Zacharakis, A., & Baron, R. A. (2003). VCs' decision processes: Evidence suggesting more experience may not always be better. *Journal of Business Venturing*, 18(3), 381–401. [https://doi.org/10.1016/S0883-9026\(02\)00099-X](https://doi.org/10.1016/S0883-9026(02)00099-X)
- Shu, Q., Tu, Q., & Wang, K. (2011). The impact of computer self-efficacy and technology dependence on computer-related technostress: A social cognitive theory perspective. *International Journal of Human-Computer Interaction*, 27(10), 923–939. <https://doi.org/10.1080/10447318.2011.555313>

- Sigala, M., & Chalkiti, K. (2015). Knowledge management, social media and employee creativity. *International Journal of Hospitality Management*, 45, 44–58. <https://doi.org/10.1016/j.ijhm.2014.11.003>
- Simon, F., & Tossan, V. (2018). Does brand-consumer social sharing matter? A relational framework of customer engagement to brand-hosted social media. *Journal of Business Research*, 85, 175–184. <https://doi.org/10.1016/j.jbusres.2017.12.050>
- Snijders, T. A. B., & Bosker, R. J. (1999). *Multilevel analysis: An introduction to basic and advanced multilevel modeling*. Sage.
- Sonnentag, S., Mojza, E. J., Demerouti, E., & Bakker, A. B. (2012). Reciprocal relations between recovery and work engagement: The moderating role of job stressors. *Journal of Applied Psychology*, 97(4), 842–853. <https://doi.org/10.1037/a0028292>
- Sonnentag, S., Reinecke, L., Mata, J., & Vorderer, P. (2018). Feeling interrupted – Being responsive: How online messages relate to affect at work. *Journal of Organizational Behavior*, 39(3), 369–383. <https://doi.org/10.1002/job.2239>
- Soucek, R., & Moser, K. (2010). Coping with information overload in email communication: Evaluation of a training intervention. *Computers in Human Behavior*, 26(6), 1458–1466. <https://doi.org/10.1016/j.chb.2010.04.024>
- Spector, P. E., & Goh, A. (2001). The role of emotions in the occupational stress process. In P. L. Perrewé & D. C. Ganster (Eds.), *Research in occupational stress and well-being: Exploring theoretical mechanisms and perspectives* (pp. 195–232). JAI Press/Elsevier. [https://doi.org/10.1016/S1479-3555\(01\)01013-7](https://doi.org/10.1016/S1479-3555(01)01013-7)
- Stamper, C. L., & Van Dyne, L. (2001). Work status and organizational citizenship behavior: A field study of restaurant employees. *Journal of Organizational Behavior*, 22(5), 517–536. <https://doi.org/10.1002/job.100>

- Steininger, D. M. (2019). Linking information systems and entrepreneurship: A review and agenda for IT-associated and digital entrepreneurship research. *Information Systems Journal*, 29(2), 363–407. <https://doi.org/10.1111/isj.12206>
- Stewart, T. R. (1988). Judgment analysis: Procedures. In B. Brehmer & C. R. B. Joyce (Eds.), *Advances in psychology* (Vol. 54, pp. 41–74). North-Holland. [https://doi.org/10.1016/S0166-4115\(08\)62170-6](https://doi.org/10.1016/S0166-4115(08)62170-6)
- Stich, J. F., Farley, S., Cooper, C., & Tarafdar, M. (2015). Information and communication technology demands: Outcomes and interventions. *Journal of Organizational Effectiveness: People and Performance*, 2(4), 327–345. <https://doi.org/10.1108/JOEPP-09-2015-0031>
- Stock, R., & Groß, M. (2016). How does knowledge workers' social technology readiness affect their innovative work behavior? In T. X. Bui & R. H. Sprague (Eds.), *Proceedings of 49th Hawaii International Conference on System Sciences* (pp. 2166–2175). Institute of Electrical and Electronics Engineers. <https://doi.org/10.1109/HICSS.2016.273>
- Suh, A., & Lee, J. (2017). Understanding teleworkers' technostress and its influence on job satisfaction. *Internet Research*, 27(1), 140–159. <https://doi.org/10.1108/IntR-06-2015-0181>
- Sun, J., & Teng, J. T. C. (2017). The construct of information systems use benefits: Theoretical explication of its underlying dimensions and the development of a measurement scale. *International Journal of Information Management*, 37(5), 400–416. <https://doi.org/10.1016/j.ijinfomgt.2017.04.010>
- Tarafdar, M., Cooper, C. L., & Stich, J. F. (2019). The technostress trifecta-techno eustress, techno distress and design: Theoretical directions and an agenda for research. *Information Systems Journal*, 29(1), 6–42. <https://doi.org/10.1111/isj.12169>

- Tarafdar, M., Pullins, E. B., & Ragu-Nathan, T. S. (2015). Technostress: Negative effect on performance and possible mitigations. *Information Systems Journal*, 25(2), 103–132. <https://doi.org/10.1111/isj.12042>
- Tarafdar, M., Tu, Q., & Ragu-Nathan, T. S. (2010). Impact of technostress on end-user satisfaction and performance. *Journal of Management Information Systems*, 27(3), 303–334. <https://doi.org/10.2753/MIS0742-1222270311>
- Tarafdar, M., Tu, Q., Ragu-Nathan, T. S., & Ragu-Nathan, B. S. (2011). Crossing to the dark side: Examining creators, outcomes, and inhibitors of technostress. *Communications of the ACM*, 54(9), 113–120. <https://doi.org/10.1145/1995376.1995403>
- Taris, T. W., Schreurs, P. J., & van Iersel-van Silfhout, I. J. (2001). Job stress, job strain, and psychological withdrawal among Dutch university staff: Towards a dual process model for the effects of occupational stress. *Work & Stress*, 15(4), 283–296. <https://doi.org/10.1080/02678370110084049>
- Teo, T. S. H., Lim, V. K. G., & Lai, R. Y. C. (1999). Intrinsic and extrinsic motivation in internet usage. *Omega*, 27(1), 25–37. [https://doi.org/10.1016/S0305-0483\(98\)00028-0](https://doi.org/10.1016/S0305-0483(98)00028-0)
- Tilson, D., Lyytinen, K., & Sørensen, C. (2010). Digital infrastructures: The missing IS research agenda. *Information Systems Research*, 21(4), 748–759. <https://doi.org/10.1287/isre.1100.0318>
- Treem, J. W., & Leonardi, P. (2012). Social media use in organizations: Exploring the affordances of visibility, editability, persistence, and association. *Communication Yearbook*, 36(1), 143–189. <https://doi.org/10.1080/23808985.2013.11679130>
- Trougakos, J. P., Hideg, I., Cheng, B. H., & Beal, D. J. (2014). Lunch breaks unpacked: The role of autonomy as a moderator of recovery during lunch. *Academy of Management Journal*, 57(2), 405–421. <https://doi.org/10.5465/amj.2011.1072>

- Tu, Q., Wang, K., & Shu, Q. (2005). Computer-related technostress in China. *Communications of the ACM*, 48(4), 77–81. <https://doi.org/10.1145/1053291.1053323>
- Turel, O., Serenko, A., & Bontis, N. (2011). Family and work-related consequences of addiction to organizational pervasive technologies. *Information & Management*, 48(2–3), 88–95. <https://doi.org/10.1016/j.im.2011.01.004>
- Turró, T., Urbano, D., & Peris-Ortiz, M. (2014). Culture and innovation: The moderating effect of cultural values on corporate entrepreneurship. *Technological Forecasting and Social Change*, 88, 360–369. <https://doi.org/10.1016/j.techfore.2013.10.004>
- van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, 28(4), 695–704. <https://doi.org/10.2307/25148660>
- van de Ven, A. H. (1986). Central problems in the management of innovation. *Management Science*, 32(5), 590–607. <https://doi.org/10.1287/mnsc.32.5.590>
- Venkatesh, V. (1999). Creation of favorable user perceptions: Exploring the role of intrinsic motivation. *MIS Quarterly*, 23(2), 239–260. <https://doi.org/10.2307/249753>
- Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating perceived behavioral control, computer anxiety and enjoyment into the technology acceptance model. *Information Systems Research*, 11(4), 342–365. <https://doi.org/10.1287/isre.11.4.342.11872>
- Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273–315. <https://doi.org/10.1111/j.1540-5915.2008.00192.x>
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>

- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Volery, T., Müller, S., Oser, F., Naepflin, C., & del Rey, N. (2013). The impact of entrepreneurship education on human capital at upper-secondary level. *Journal of Small Business Management*, 51(3), 429–446. <https://doi.org/10.1111/jsbm.12020>
- von Briel, F., Davidsson, P., & Recker, J. (2018). Digital technologies as external enablers of new venture creation in the IT hardware sector. *Entrepreneurship Theory and Practice*, 42(1), 47–69. <https://doi.org/10.1177/1042258717732779>
- Warr, P., Bindl, U. K., Parker, S. K., & Inceoglu, I. (2014). Four-quadrant investigation of job-related affects and behaviours. *European Journal of Work and Organizational Psychology*, 23(3), 342–363. <https://doi.org/10.1080/1359432X.2012.744449>
- Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, 54(6), 1063–1070. <https://doi.org/10.1037//0022-3514.54.6.1063>
- Weinberger, E., Wach, D., Stephan, U., & Wegge, J. (2018). Having a creative day: Understanding entrepreneurs' daily idea generation through a recovery lens. *Journal of Business Venturing*, 33(1), 1–19. <https://doi.org/10.1016/j.jbusvent.2017.09.001>
- Weiss, H. M., & Cropanzano, R. (1996). Affective events theory: A theoretical discussion of the structure, causes and consequences of affective experiences at work. In B. M. Staw & L. L. Cummings (Eds.), *Research in organization behavior* (Vol. 18, pp. 1–74). JAI Press.
- West, M. A. (2002). Sparkling fountains or stagnant ponds: An integrative model of creativity and innovation implementation in work groups. *Applied Psychology*, 51(3), 355–387. <https://doi.org/10.1111/1464-0597.00951>

- West, M. A., & Farr, J. L. (1990). Innovation at work. In M. A. West & J. L. Farr (Eds.), *Innovation and creativity at work: Psychological and organizational strategies* (p. 3–13). John Wiley & Sons.
- Wharton, A. S., & Blair-Loy, M. (2002). The “overtime culture” in a global corporation: A cross-national study of finance professionals' interest in working part-time. *Work and Occupations*, 29(1), 32–63. <https://doi.org/10.1177/0730888402029001003>
- Williamson, A. J., Battisti, M., Leatherbee, M., & Gish, J. J. (2019). Rest, zest, and my innovative best: Sleep and mood as drivers of entrepreneurs' innovative behavior. *Entrepreneurship Theory and Practice*, 43(3), 582–610. <https://doi.org/10.1177/1042258718798630>
- Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. *Educational and Psychological Measurement*, 73(6), 913–934. <https://doi.org/10.1177/0013164413495237>
- Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, 67, 221–232. <https://doi.org/10.1016/j.chb.2016.10.028>
- Wu, J., Wang, N., Mei, W., & Liu, L. (2017). Does techno-invasion trigger job anxiety? Moderating effects of computer self-efficacy and perceived organizational support. *WHICEB 2017 Proceedings*, 241–250. <https://aisel.aisnet.org/whiceb2017/42>
- Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2009). Reciprocal relationships between job resources, personal resources, and work engagement. *Journal of Vocational behavior*, 74(3), 235–244. <https://doi.org/10.1016/j.jvb.2008.11.003>

- Yan, Y., Davison, R. M., & Mo, C. (2013). Employee creativity formation: The roles of knowledge seeking, knowledge contributing and flow experience in Web 2.0 virtual communities. *Computers in Human Behavior*, 29(5), 1923–1932. <https://doi.org/10.1016/j.chb.2013.03.007>
- Ye, H., & Kankanhalli, A. (2018). User service innovation on mobile phone platforms: Investigating impacts of lead user status, toolkit support, and design autonomy. *MIS Quarterly*, 42(1), 165–187. <https://doi.org/10.25300/MISQ/2018/12361>
- Yoo, Y., Boland, R. J., Jr., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science*, 23(5), 1398–1408. <https://doi.org/10.1287/orsc.1120.0771>
- Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, 21(4), 724–735. <https://doi.org/10.1287/isre.1100.0322>
- Yuan, F., & Woodman, R. W. (2010). Innovative behavior in the workplace: The role of performance and image outcome expectations. *Academy of Management Journal*, 53(2), 323–342. <https://doi.org/10.5465/amj.2010.49388995>
- Yukl, G. (2013). *Leadership in organizations* (8th ed.). Pearson Education.
- Zacher, H., Chan, F., Bakker, A. B., & Demerouti, E. (2015). Selection, optimization, and compensation strategies: Interactive effects on daily work engagement. *Journal of Vocational Behavior*, 87, 101–107. <https://doi.org/10.1016/j.jvb.2014.12.008>
- Zacher, H., & Winter, G. (2011). Eldercare demands, strain, and work engagement: The moderating role of perceived organizational support. *Journal of Vocational Behavior*, 79(3), 667–680. <https://doi.org/10.1016/j.jvb.2011.03.020>

- Zampetakis, L. A., Beldekis, P., & Moustakis, V. S. (2009). “Day-to-day” entrepreneurship within organisations: The role of trait emotional intelligence and perceived organisational support. *European Management Journal*, 27(3), 165–175. <https://doi.org/10.1016/j.emj.2008.08.003>
- Zhang, Y., & Chen, C. C. (2013). Developmental leadership and organizational citizenship behavior: Mediating effects of self-determination, supervisor identification, and organizational identification. *The Leadership Quarterly*, 24(4), 534–543. <https://doi.org/10.1016/j.leaqua.2013.03.007>
- Zittrain, J. L. (2006). The generative internet. *Harvard Law Review*, 119(7), 1974–2040. <https://doi.org/10.1145/1435417.1435426>
- Zittrain, J. L. (2007). Saving the internet. *Harvard Business Review*, 85(6), 49–59. <https://hbr.org/2007/06/saving-the-internet>
- Zittrain, J. L. (2008). *The future of the internet and how to stop it*. Yale University Press.

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Work Experience

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