



# Micro-foundations of digital innovation capability – A mixed method approach to develop and validate a multi-dimensional measurement instrument

Julia Kroh<sup>a,\*</sup>, Dietfried Globocnik<sup>b</sup>, Carsten Schultz<sup>a</sup>, Frederike Holdhof<sup>a</sup>, Søren Salomo<sup>c</sup>

<sup>a</sup> Kiel University, Institute for Innovation Research, Westring 425, 24118 Kiel, Germany

<sup>b</sup> Alpen-Adria Universität, Department of Innovation Management and Entrepreneurship, Universitaetsstrasse 65-67, 9020 Klagenfurt, Austria

<sup>c</sup> Berlin Institute of Technology, Institute for Technology and Innovation Management, Straße des 17. Juni 135, 10623 Berlin, Germany

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## ABSTRACT

Digital innovation refers to the creation or adoption value-adding novelty through the incorporation of digital technology. Digital innovation challenges established product-centric companies whose innovation management capabilities are insufficient to manage the reconfiguration and transformation necessary for digital innovation and technology. Recent research has introduced different concepts of for example, digital readiness, digitalization capabilities, and digital innovation readiness. However, these concepts have two shortcomings for use in practice and empirical research: most concepts are theoretical in nature, with limited empirically validated measures. As such, this study takes a dynamic capability view to synthesize prior literature on the organizational antecedents of digital innovation and develops a framework for the micro-foundations of digital innovation capability. By applying a mixed-method approach, existing concepts are extended through qualitative research and then translated into a multi-dimensional measurement instrument. This multi-item operationalization is then subjected to scale validation using quantitative research methods. The results show that a company's digital innovation capability is founded upon seven micro-foundations – digital focus, digital innovation process, digital mindset, digital innovation network, digital technology capability, data management, and overcoming digital innovation resistance – that facilitate established companies in sensing, seizing, and reconfiguring digital innovation.

## 1. Introduction

Digital innovation refers to “the creation or adoption, and exploitation of an inherently unbounded, value-adding novelty through the incorporation of digital technology” (Hund et al., 2021:6) whereas the possible outcomes can take the form of, for instance, new products, services, processes, or business models. New digital technologies, such as artificial intelligence, cloud, mobile, social media, and business analytics, significantly impact how an organization creates and captures value (Lanzolla et al., 2020), operates its routine and innovation processes (Füller et al., 2022; Rauch et al., 2020), and organizes the workplace (Marsh et al., 2022). Many digital technologies are accessible from third parties on demand, have numerous flexible and scalable application areas, and enable new linkages with customers, suppliers,

and other network partners (Lokuge et al., 2019).

Digital innovation often results in a new combination of digital and physical components drawing on digitalization (i.e., the encoding of analog information into a digital format), which allows products to become programmable, addressable, sensible, communicable, memorable, traceable, and associable (Yoo, 2010). Digital innovations offer companies the possibility of establishing layered product architectures, consisting of device, network, service, and content layers (Benkler, 2008), and customers can be provided with digital platform-based services (Hilbolling et al., 2020). This also facilitates new market players to compete, or even change the competitive landscape of an industry (Autio et al., 2018). Consequently, digital innovations have the potential to disrupt the product-centric business models of established companies in industries such as mechanical engineering, which have traditionally

\* Corresponding author.

E-mail addresses: [kroh@bwl.uni-kiel.de](mailto:kroh@bwl.uni-kiel.de) (J. Kroh), [dietfried.globocnik@aau.at](mailto:dietfried.globocnik@aau.at) (D. Globocnik), [schultz@bwl.uni-kiel.de](mailto:schultz@bwl.uni-kiel.de) (C. Schultz), [holdhof@bwl.uni-kiel.de](mailto:holdhof@bwl.uni-kiel.de) (F. Holdhof), [salomo@tu-berlin.de](mailto:salomo@tu-berlin.de) (S. Salomo).

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developed, manufactured, and sold physical products by blurring the boundaries between digital and non-digital business models (de Massis et al., 2018; Williams et al., 2022). Therefore, this article addresses the following research question: *Which micro-foundations build a digital innovation capability for established companies and therewith enable them to reinterpret and reconfigure their knowledge, resources, routines, and capabilities to take advantage of the changes caused by new digital technologies?*

The layered nature of digital technology increases the complexity of innovation activities (Tuomi, 2002). Digital innovation requires stakeholder contributions to a heterogeneous ecosystem inside and outside a company (Nambisan et al., 2019). This increases the requirement for cross-functional collaboration between different departments and disciplines. Digital innovation also requires a wide spectrum of partners, including collaborations with specialized vendors (hardware, software, and IT solutions), suppliers, and customers in an open ecosystem (Abrell et al., 2016; Füller et al., 2022; Yoo et al., 2010). Consequently, digital innovation and the underlying technologies are often not controlled by a single company but involve different – and sometimes even temporarily – affiliated partners (Lyytinen et al., 2016; Yoo et al., 2012). Such digital innovation and value creation networks not only add further complexity to innovation activities, but also create uncertainty about relevant partners, competitors, and potential customers (Wirtz et al., 2022), and how to organize innovation in such an environment (Hanelt et al., 2021). Therefore, traditional innovation management practices might not suffice for digital innovation (Rindfleisch et al., 2017), which may require a specific set of capabilities to succeed (Appio et al., 2021; Dąbrowska et al., 2022).

These characteristics of digital innovation are particularly critical for established companies, which are the focus of this study. Past research reports that despite existing innovation capabilities for non-digital products, services, and processes. Incumbents tend to struggle to develop innovations in general (König et al., 2013), especially digital ones, which fundamentally change opportunities to create value (Ceipek et al., 2021; Rummel et al., 2022). Digital startups and software companies have a native, default, and foundational focus on digital businesses. Their digital innovation capabilities enabling them to start and grow a purely digital business, which are built from scratch, might not represent those that are necessary for established companies. They require a set of digital innovation capabilities that enable a continuous reinterpretation of the status quo; reconfiguring their own resource base, routines, and capabilities; and transforming them based on the newly identified opportunities provided by created or emerging digital technologies (Dąbrowska et al., 2022). This digital innovation capability is a pre-requisite for generating the new digital innovations necessary to enter, develop, and grow established companies' digital businesses.

In the search for critical capabilities enabling digital innovation in established companies, recent research has introduced the concepts of digital readiness (Gfrerer et al., 2021), digitalization capabilities (Annarelli et al., 2021), digital innovation readiness (Lokuge et al., 2019), organization-level factors of digital transformation (Dąbrowska et al., 2022), digital innovation management (Nambisan et al., 2017), competing digital innovation concerns (Svahn et al., 2017a), strategic digital innovation orientation (Kindermann et al., 2020), and AI-based innovation management (Füller et al., 2022). These concepts have two shortcomings for use in practice and empirical research: most concepts are theoretical in nature, with limited empirically validated measures (e. g., Lokuge et al., 2019). Furthermore, these concepts organize various resources, capabilities, and competences, similar to the traditional innovation literature, molded into the digital innovation space. Given the particular context of established product-centric companies that must transform, rather than improve, their existing businesses due to new digital technologies, the concept of digital innovation capability for established companies must consider what is needed to enable them to reinterpret and reconfigure their knowledge, resources, routines, and capabilities. Therefore, we aim to develop and validate a new conceptualization of digital innovation capability by taking a dynamic

capability view (Teece, 2007) and determining the micro-foundations necessary to transform—that is, to sense, seize, and reconfigure—digital innovation opportunities and resources (Björkdahl, 2020).

By applying a mixed-method approach, we revisit the existing literature to extract the relevant micro-foundations of digital innovation capability that enable a company's digital change and renewal. The initial conceptualization was then tested and refined through a qualitative study on a sample of established companies. The qualitative data also supported the subsequent development of a multi-dimensional multi-item measurement instrument, which was then subjected to quantitative scale validation using survey data collected from two different geographical regions. Responding to the call for research on new realities in the digital age (Menz et al., 2021) and the foundations necessary to innovate in the digital world (Dąbrowska et al., 2022), we contribute to the literature by determining seven micro-foundations of digital innovation capability for established companies: digital focus, digital innovation process, digital mindset, digital innovation network, digital technology capability, data management, and overcoming digital innovation resistance. Furthermore, we provide future research with a reliable and valid measurement instrument tested across different regions for psychometric equivalence.

The next section explains the dynamic capability view, micro-foundations of the digital innovation capability and includes a structured overview of prior conceptualizations of digital innovation capabilities. Following this, the methodology for the scale development is presented. The section thereafter describes the data collection, analysis, and the results of the qualitative study, followed by data collection, analysis, and results of the quantitative study, presenting the digital innovation capability scale. The final section contains the discussion, implications, and future research.

## 2. Theoretical background

### 2.1. A dynamic capability view of digital innovation capability

The dynamic capability view explains how companies can adapt and thrive in a rapidly changing business environment and sustain competitive advantage. Therefore, the approach fits well within the context of established product-centric companies that transform their businesses into digital spaces. This approach proposes three organizational-level capabilities that enable this dynamic adaptation. Sensing involves continuously scanning the external environment for new opportunities and threats. Seizing refers to grasping opportunities through innovation, creativity, or strategic alliances. Reconfiguring is the ability to change an organization's structure, processes, and resource base to successfully exploit new opportunities (Teece et al., 1997). In addition to the capabilities themselves, a company's success depends on how managers use these dynamic capabilities (Eisenhardt and Martin, 2000).

Therefore, we interpret digital innovation capability as a dynamic capability rather than a contextualized form of “functional” innovation capability. The latter also includes the improvement and development of existing products, services, and business processes that operate under stable conditions. “Dynamic” capabilities refer to the ability to create, extend, and modify a company's knowledge and resource base to respond to changes in (or even proactively shape) the environment and competitive landscape (Helfat et al., 2007), as required when established product-centric companies must reconfigure to transform into hybrid or digital businesses. Micro-foundations of a dynamic capability are the skills, procedures, mechanisms, structures, and resources underlying sensing, seizing, and reconfiguring capabilities. They are rooted in the cognitive and behavioral processes of individuals within an organization, including their learning processes, problem-solving abilities, and decision-making styles. They also involve the social and cultural aspects of the organization, such as the norms and values that shape the interactions between individuals and teams. Additionally, the micro-

foundations of dynamic capabilities include organizational structures and systems that support learning and adaptation (Teece, 2007).

Consequently, the conceptualization of digital innovation capability as a dynamic capability requires the identification of relevant micro-foundations that enable established companies to sense, seize, and reconfigure, to take advantage of the new opportunities provided by digital technologies.

## 2.2. Micro-foundations of digital innovation capability

Table 1 provides an overview of prior concepts about the organizational-level factors of established companies that are necessary to utilize digital technologies. The table therefore includes articles that focus on digital readiness and digital innovation capabilities.

Digital readiness (Gfrerer et al., 2021) emphasizes organizational-level factors that enable digital transformation, including digital empowerment and involvement of employees by managers, appropriate organizational structures, digitally experienced managers, willingness to act on digital trends, and absence of barriers, such as a lack of innovation culture or technology skills, budgetary or legal restrictions and leadership buy-in. Annarelli et al. (2021) conceptualized *digitalization capabilities* enabling digital transformation as a higher-order dynamic capability with underlying capabilities like formalized routines that effectively utilize digital resources. The management of digital ecosystem partnerships and supply chain integration enables the organization to sense new opportunities, foster digital processes, to use IT resources, and to integrate them with non-IT resources. Managers' cognition of the relevance of change through digitalization determines how the company (i) seizes digital capabilities, (ii) reconfigures the resources to enable digital innovation in a timely manner, and (iii) acts promptly on newly observed trends in the digital environment through the help of improvisational capabilities, thereby enabling the company to reconfigure its digital resources and routines. In their literature review, Dąbrowska et al. (2022) investigate the phenomenon of digital transformation at the individual, organizational, ecosystem, and geopolitical levels. *Organizational-level digital transformation* requires the company to consider, or respond to digital technologies in four main areas:

- i) a change in corporate strategy due to the significant changes caused by digital technologies on internal processes, product offering, value chain partners, and competitive landscape;
- ii) organizational designs that facilitate the orchestration, collaboration, and coordination of internal and external partners, which are necessary to cope with the additional complexity of creating and implementing digital innovations;
- iii) digital capabilities to use new technologies for faster information processing and better, more objective decision-making, based on data; and
- iv) changes in value creation and logic, to cope with additional complexity when orchestrating multiple ecosystem partners and taking advantage of new opportunities on how to lower competitive pressure.

In their conceptual work on *digital innovation management*, Nambisan et al. (2017) argued that digitalization challenges the assumptions of traditional innovation management. The authors suggest new “logics,” rather than specific skills or capabilities, as necessary to address these challenges: dynamic problem-solution pairing, instead of linear innovation processes, wherein digital innovation is: (i) a constant process of generation, merging, and refinement to achieve need-solution fit; (ii) socio-cognitive sensemaking necessary for all actors to frame the potential and value of digital technologies and change their understanding of possible innovation outcomes; (iii) technology affordability and constraints, which consider that the same digital technology can be repurposed by different actors or used to produce different innovation

outcomes; (iv) orchestration emphasizing the role of digital technologies to integrate the activities of diverse internal and external parties. In their *organizational setup for AI-based innovation management* of the company, Füller et al. (2022) determined three factors: (i) employees skilled in digital and AI technologies, (ii) organizational structures allowing rapid and effective response to major transformations and integration of internal and external actors for collaboration, and (iii) an innovation strategy with ambitious AI goals and program activities to achieve them.

The concept of *strategic digital innovation orientation* (Kindermann et al., 2020) defines four dimensions that capture the strategic posture of a company concerning digital innovation: digital technology scope describes the company-specific set of technologies that determine the extent to which digitally enabled value for customers can be created; digital capabilities are the organizational routines for a set of technologies rooted in employees' technology skills and knowledge; digital ecosystem coordination enables effective interaction with other stakeholders on platforms in open technology ecosystems; and digital architecture configuration describes how the company organizes its technological infrastructure and working processes to effectively utilize and repurpose technologies. To develop the concept of *digital innovation readiness*, Lokuge et al. (2019) considered an organizational change perspective and identified factors that determine an organization's readiness for digital innovation. These entail resources (innovation resources and IT infrastructure), a facilitating climate for the integration of IT into innovation considerations and motivation to engage in innovation in general, partnerships with external experts, and clear strategic goals for digital innovations. While exploring the primary competing digital innovation concerns of incumbent companies, and the strategies to remedy them, Svahn et al. (2017a,b) highlight four areas: the development of new digital capabilities without jeopardizing established product innovation practices; a balance between continuous improvement of existing solutions by leveraging digital technology, and new development of products and services; a balance between existing internal work arrangements and engaging external partners and resources; governance structures with less hierarchical control; and more flexibility to freely explore digital opportunities.

These conceptualizations focus on different facets of organizational change driven by digital technologies (e.g., digitalization, digital transformation, and AI in innovation management) but overlap in how they organize the necessary company-level skills, procedures, mechanisms, structures, and resources. To determine the relevant micro-foundations of digital innovation capability, we synthesize these frameworks, through a dynamic capability lens, into five factors that enable an established company to sense, seize, and transform:

*Digital focus* emphasizes explicit digital innovation goals and a formal digital innovation strategy (Lokuge et al., 2019) to guide employees in their innovation-related decisions and activities. The technological scope that directly influences the underlying business model (Schallmo et al., 2022) and might require a full reconfiguration of a company's strategy (Dąbrowska et al., 2022; D'Ippolito et al., 2019), specifically, needs to be defined. Digital focus is also expressed in clear roles and responsibilities for digital innovations, as well as in a flexible infrastructure, and financial and human resources necessary for implementation (Chen et al., 2017; Füller et al., 2022). Therefore, digital focus is a micro-foundation of digital innovation capability that defines search areas for sensing opportunities, guides strategic innovation portfolios and project selection decisions for seizing opportunities, and reconfigures them by aligning resources with the digital innovation strategy.

The *digital innovation process* is characterized by mechanisms that support agile and flexible development processes. Organizational agility, adaptability, and ambidexterity are crucial for quickly responding to changes in the environment, and are particularly relevant for digital innovation output and economic performance (Del Giudice et al., 2021; Troise et al., 2022). Moderate levels of formal control, coupled with agile and flexible innovation process designs, seem particularly promising for digital innovation development (Lane and Lubatkin, 1998;

**Table 1**  
Overview of prior conceptualizations of digital innovation capabilities.

Concept/Author	Research objective	Key dimensions	Research method	Theoretical foundation
Digital readiness Gfrerer et al. (2021)	Systematic differences in digital readiness perceptions among hierarchical levels	Organizational level - Digital empowerment - Digital involvement - Appropriate organizational structures - Digitally experienced managers - Willingness to act on digital trends - Innovation barriers and reaction speed Individual level - Individual beliefs (readiness, attitudes) - Individual competences (knowhow, skills)	Empirical (banking industry)	Change readiness framework
Digitalization capabilities Annarelli et al. (2021)	Identification of antecedents, consequences, and capabilities underlying higher-order digitalization capability	Sensing - Ecosystem capabilities - Supply chain process integration Seizing - Employing heterogeneous resources - Deploying IT - Role of managerial cognition driving change - Organizing IT capabilities Reconfiguring - Improvisational capabilities - Scanning evolution of digital environment - Timely reconfiguration of resources	Literature review (co-citation analysis)	Dynamic capability view
Digital innovation readiness Lokuge et al. (2019)	Conceptualization of a formative multi-dimensional construct for organizational readiness enabling digital innovation	- Resource readiness - IT readiness - Cognitive readiness - Partnership readiness - Innovation valance - Cultural readiness - Strategic readiness - Dynamic problem-solution pairing - Socio-cognitive sense making - Technology affordances and constraints - Orchestration - Strategy and strategic response - Change and organizational design - Decision-making capabilities - Change in value creation and capture	Mixed methods approach (qualitative and quantitative data)	Organizational readiness for change theory
Digital innovation management Nambisan et al. (2017)	Theorize digital innovation management	Competing Concerns: - Capability: Existing vs. requisite - Innovation focus: Product vs. process - Collaboration: Internal vs. external - Governance: Control vs. flexibility	Conceptual	Diverse innovation theories
Organizational-level digital transformation Dąbrowska et al. (2022)	Development of multi-level framework for digital transformation and agenda for future research	- Digital technology scope - Digital capabilities - Digital ecosystem coordination - Digital architecture configuration	Conceptual	Diverse digital transformation approaches
Competing digital innovation concerns Svahn et al. (2017a,b)	Digital innovation concerns and how to manage them		Longitudinal case study	
Strategic digital innovation orientation Kindermann et al. (2020)	Development of holistic concept of an organization's strategic orientation concerning digital innovation and transformation initiatives		Computer-aided text analysis of shareholder letters from US-based companies over 16 years	Resource-based view

(continued on next page)



Table 1 (continued)

Concept/Author	Research objective	Key dimensions	Research method	Theoretical foundation
Organizational setup for AI-based innovation management Füller et al. (2022)	Impact of AI on innovation management and required organizational setup; innovation manager segmentation	- Digital and AI skills of employees - Organizational structures - Innovation strategy	Empirical	Innovation management literature

Schultz et al., 2019; Svahn et al., 2017b). Agility allows for the constant consideration and integration of new digital innovation opportunities in the innovation process, wherein their potential is explored through improvisation (Annarelli et al., 2021) as well as rapid iterative experimentation and development cycles (Nambisan et al., 2017; Peña Häufler et al., 2021). Therefore, a flexible digital innovation process that supports the constant search for and exploration of digital innovations provides a micro-foundation for sensing and seizing opportunities.

A *digital mindset* considers that possessing resources and practices for digital innovation may not be sufficient. It requires shared understanding and knowledge among employees and managers about the potential of digital technologies, to recognize, and respond to, emerging trends (Huber et al., 2020; Nambisan et al., 2017). Profound and broadly shared digital knowledge increases employees' self-efficacy in using digital technologies and, therefore, their digital innovativeness (Mancha and Shankaranarayanan, 2020). Furthermore, an entrepreneurial climate is needed so that employees are motivated and empowered to proactively explore new digital opportunities (Lokuge et al., 2019; Dąbrowska et al., 2022). Therefore, a digital mindset is a relevant micro-foundation for seizing digital opportunities.

*Digital technology adoption and data management* subsume the resources and activities necessary to use data for value creation. Digital innovation requires not only appropriate physical resources in the form of the necessary IT infrastructure and digital platforms (Sedera et al., 2016; Yoo et al., 2012), but also the ability to utilize them. The latter refers to IT-enabled routines and the ability to collect, analyze, and interpret data from different sources (Huber et al., 2020). Clear responsibilities and coordination mechanisms orchestrate the process of accessing and generating data for interpretation. This should eventually support more objective, data-driven decision making (Dąbrowska et al., 2022). Furthermore, IT infrastructure must be adapted to respond to changes in the technological environment (Chen et al., 2017). This requires the company to develop the ability to recognize new digital technologies and the value of new data sources. Therefore, digital technology adoption and data management is an essential micro-foundation of digital innovation capability, as it supports, (i) sensing new opportunities by creating data-driven insights, (ii) seizing opportunities by improving innovation decision-making, and (iii) transforming by leveraging new businesses through new data sources, and constantly renewing the digital technology base underlying digital innovation.

*Digital innovation network* accounts for the need for companies to engage in digital innovation and cooperate with different partners, including IT vendors, consultants, suppliers, complementors, and customers (Abrell et al., 2016). This requires mechanisms to assess which technology should originate internally (Muehlburger et al., 2022), and which should originate externally, from partners, if internal knowledge is insufficient (Hanelt et al., 2021; Kindermann et al., 2020). Therefore, a company must open up its innovation process and facilitate collaboration with external partners. However, in the context of digital innovation, such collaborations differ from traditional customer-supplier relationships. Partnerships are often temporary, non-exclusive, and not controlled by a single company (Lyytinen et al., 2016). For instance, digital platforms bring together an ecosystem of heterogeneous actors who innovate and collaboratively create value (Yoo et al., 2012). This requires the ability to orchestrate the partners of such heterogeneous networks (Svahn et al., 2017b; Urbinati et al., 2020), by cultivating

governance structures that allow collaborative innovation, knowledge sharing, and joint value creation and capture (e.g., Kindermann et al., 2020). Therefore, the ability to establish and orchestrate a network of partners is a micro-foundation of digital innovation capability that supports sensing new opportunities by learning about new digital technological and business possibilities from outside the company, seizing these opportunities through collaboration with external partners, and transforming the company's structures, processes, and resources by organizing them in ecosystems.

This literature-based conceptualization of the micro-foundations of digital innovation capability is the initial point for subsequent scale development.

### 3. Method for scale development

We used an exploratory sequential mixed method approach (Creswell, 1994), thereby following an established scale development procedure (Churchill, 1979; Hinkin, 1995). Accordingly, this study builds on our initial literature-based conceptualization of the micro-foundations of digital innovation capability. Due to the novelty of the phenomenon and our chosen theoretical lens, we conducted a qualitative study (Study 1) to derive and detail the specific micro-foundations that need to be included in our measurement instrument, following the suggested evaluation guidelines of qualitative research (Goffin et al., 2019). This method allowed us to explore in depth the relevance and limitations of our initial conceptualization of digital innovation capability, and to operationalize the measurement instrument (Eisenhardt, 1989; Leonard-Barton, 1990). The qualitative analysis results formed the basis for developing the items of the multi-dimensional measure of our digital innovation capability scale. We then validated the scale by drawing on quantitative survey data (Study 2), following the established approach of scale purification and the assessment of structural validity, convergent validity, and structural invariance between different geographical contexts (Hinkin, 1998).

#### 3.1. Study 1: qualitative scale development

##### 3.1.1. Procedure and sample

To this end, we considered three relevant cases for qualitative scale development (Cappa et al., 2022) pertaining to three established companies in North Germany. We selected these three cases for the following reasons. (i) All established companies have already started to shift their business focus to include digital technologies in their products, and offer digital services. (ii) As the majority of other medium-sized companies have a long tradition of selling physical products and certainly face challenges when they start using digital technologies, they tend to be risk averse (Ceipek et al., 2021). Thus, they reflect the transformation from analogous to digital innovation. (iii) The three cases share important similarities (e.g., company history and German headquarters' location) but show important differences (e.g., industry, number of employees, current digital innovation ability, and innovation success), which is crucial for the external validity of the results (Flick et al., 2004). Consequently, the nature of the three cases is consistent with the aim of analyzing and discussing the phenomenon (Siggelkow, 2007). Therefore, we employed maximum variation sampling and analyzed cases covering a spectrum of lenses, regarding the phenomenon investigated (Eisenhardt and Graebner, 2007). Table 2 summarizes the

**Table 2**  
Case characteristics of qualitative analysis.

Company	Industry	Number of employees (FTE)	Number of interviews	Interviewees' functional backgrounds	Interviewees' hierarchical levels
A	Marine industry	550	6	Product and Project Management, Business Development, HR	Middle and top management
B	Medical technology industry	1960	6	R&D, Quality Management, Operations, Controlling	Middle management and employees
C	Mechanical engineering	1050	6	Product and Project Management, Sales, R&D	Top, middle management, and employees

characteristics of the three cases and the 18 respondents.

We conducted personal interviews lasting between 30 and 60 min each in 2019. We started with a set of open-ended questions to allow digital innovation capabilities to evolve naturally from conversations with the interviewees. We then organized our interview guidelines along the micro-foundations of digital innovation capability identified in the literature review (see Table 1).

The interview guide is shown in Appendix 1. The interviews were transcribed and subjected to qualitative content analysis using MAXQDA

2020 (VERBI Software, 2019). We developed a reference guideline comprising five main micro-foundations as categories (*digital focus*, *digital mindset*, *digital innovation process*, *digital technology and data management*, *digital innovation network*) and coded our data accordingly. The initial first-order analysis confirmed five main categories but, in addition, we inductively discovered a new category (*overcoming digital innovation resistance*) and added it to our reference guidelines. Next, we went through our data again and added subcategories to each category. Therefore, we ensured that the initial codes matched the reference

**Table 3**  
Micro-foundations based on qualitative analysis.

Micro-foundation	Digital focus	Digital innovation process	Digital mindset	Digital technology adoption and data management	Digital innovation network	Overcoming digital innovation resistance
Description	Describes the underlying strategy for digital innovation including a company's digital ambition, strategy formulation, and the availability of relevant resources	Describes the flexible and interactive innovation process necessary for digital innovation including agile innovation methods	Describes the shared understanding of digital innovations among employees facilitating awareness and proactive search for new digital opportunities	Describes availability of technology, data management competences, and ability to translate outputs into business applications	Describes the ability to collaborate with external partners for digital innovations (e. g., competitors, suppliers, customers and universities)	Describes barriers to digital innovations including resistance from employees and lack of technology availability
Facets	Formulation of a digital innovation strategy and goals; Flexibility of innovation strategy; Resources for digital innovation; Roles and responsibilities	Restructured innovation process; Agile and flexible innovation development methods; digital opportunity search	Shared understanding of digital innovation; Employee initiatives; Digital natives	Technological infrastructure; Data infrastructure; Data platforms; Ability to collect, process and interpret data; decision relevance of data	Collaboration with suppliers, competitors, customers, research institutions; Collaboration in developing core competencies	Employee resistance; Lack of skills; Technological barriers; Legal framework; Bureaucratic processes
Proof quote (s)	"We have a Vision 2025 [...], where we define that this company will move strongly toward software-based products [...] and our current hardware must be replaced step by step." (Company A) "It is important, to have a clear strategy and [...] basically, we need more speed in developing digital innovations. [...] When we recognize that we do not have the resources to develop digital innovations, [...], we have to buy them. We have to take the risk to stay competitive in the future." (Company C)	"We can buy digital technologies to develop digital technologies, of course, but when we do not have a structured innovation process, we can't use it." (Company C) "We naturally have to work with more agile, more interactive [...], and even completely new methods. Digital innovations have different requirements [...], and we need to systematically change our innovation process" (Company B) "You need to lower barriers for idea generation in the company. We [...] created a space [...], where people can meet easily to be creative, to prototype, to try out." (Company A)	"Digital innovation [...] has to get into people's heads and [...] that is a challenge for every single employee. Changing a mindset is not easy." (Company B) "The real challenge is to change the mindset in the company. We have to become more digital from within ourselves." (Company A) "Uncertainty on digital innovations gives us a lot of new opportunities. [...] Of course, we can do something wrong – by turning left or right too early or whatever. But we will definitely be on the right path and learn from our mistakes." (Company C)	"The data are the competitive advantage we have." (Company B) "It is not enough to develop a platform [...]. We have to operate them, we need to combine different data sources to propose value [...] and to have a platform-driven business model." (Company C) "There is high business potential in after-sales, because we have the data on how the customer uses our products. [...] We will probably end up with leasing or renting out certain services based on software products." (Company A)	"We [...] are working with other companies that have the core competences. We also work with universities and research institutes, [...] because we do not have the resources or skills." (Company A) "We collect a lot of input from our customers and collaborate closely with them in the innovation development." (Company B) "The nature of collaboration will change a lot; we have to pay much more attention to what competences suppliers or partners have. [...] The speed of digital innovations is extremely high and we can only profit when the whole industry collaborates on artificial intelligence." (Company C)	"Employees who work in our company for 20 to 30 years [...] fear that they are not able to cope with digital innovations." (Company B) "We still have communication problems between hardware and software developers. Hardware developers try to defend their empire [...] although software is getting more important than ever." (Company A) "The legal framework is anti-innovative. Data protection and a lot of other laws and regulations hamper digital technologies' fast market entry." (Company B)
Total number of codes	91	64	98	46	117	55

categories and changed the codes slightly, where necessary. This facilitates a more fine-grained understanding of the micro-foundation of digital innovation capabilities. Table 3 summarizes the main categories, subcategories, and example quotes. Next, we developed items for each micro-foundation.

### 3.1.2. Results

We identified six micro-foundations of established companies' digital innovation capabilities of established companies (see Table 3). While the five identified micro-foundations validated our prior conceptualization, qualitative research resulted in one additional facet.

First, *digital focus* is the company's ability to evaluate the strategic impact of digital innovation on its business model (Foss and Saebi, 2017). Our interviewees emphasized that their companies not only recognized the importance of digital innovation within their current business models but also explored it, along with business opportunities, outside their core industry. Further, they emphasized that a company needs to integrate digital innovation into its innovation goals and strategy, including financial, human resources, and strategic technology planning. This also requires defining clear roles and responsibilities for seizing digital opportunities. One interviewee stated:

*"Our business model evolves continuously. We have a written digital innovation strategy, but we still struggle to implement it in our processes. However, we need to strategically align our processes to our future markets."*

Second, we learned from respondents that the *digital innovation process* constantly considers experiments with digital innovation opportunities. Consequently, the processes should focus on flexible and agile innovation development methods. Recent research also emphasizes that incumbent companies should balance flexibility and control in their innovation processes (Svahn et al., 2017a). The need for the rapid development and protection of digital innovations is driven by the awareness of higher competitive pressure; that is, new market actors might take advantage of emerging digital business opportunities. One employee emphasized the challenge of changing the innovation development process in a company that rigidly formalized innovation processes.

*"We had centralized structures and a traditional stage-gate based innovation process. Therefore, we still use our traditional processes for digital innovation projects. Consequently, not all of our digital innovation projects are agile, although they should be. But we try to use agile methods when uncertainty increases."*

Third, the *digital mindset* emphasizes the necessity for a shared understanding of digital technologies and their potential for daily work and business. However, digital innovations increasingly contain advanced digital technologies, such as AI and big data analyses (Ardolino et al., 2016) that, on the one hand, demand new competencies from employees and, on the other hand, can weaken the long-term value of existing competencies (Huang and Rust, 2018). The interviewees mentioned that the "fear of missing something" hampered the development of digital innovation. The generativity and flexibility needed for digital innovation contrast with the rigidity of incumbent employees' routines, procedures, and beliefs (König et al., 2021). Thus, a change toward a digital mindset, wherein employees trust their competencies and feel empowered to develop digital innovations, is essential. One interviewee stated the following:

*"We have cultural problems, because many employees think that a digital output is not a value proposition. Achieving a change in the mindset is not easy, and communicating our digital strategy is a first, but not the last, step on this journey."*

Fourth, the qualitative content analysis results supported the relevance of *digital technology adoption and data management*. Physical resources are an essential prerequisite for digital technology, and data

management capability is a prerequisite for digital innovation. Companies cannot develop digital innovation without the necessary technology and databases (Yoo et al., 2012), therefore digital technology (i.e., infrastructure) and data management abilities (i.e., clear responsibility and coordination mechanisms for operational activities) are necessary to gather, analyze, and use data for innovation development. One interviewee highlighted the challenge of data management, despite a proper IT infrastructure:

*"We renewed our IT system and have a large amount of data that is a good basis to find new business opportunities. However, we still struggle to analyze the data because of its complexity."*

Fifth, the results emphasize the importance of a *digital innovation network*, referring to companies' collaboration levels within and beyond their traditional supply chain and industry, a feature that must be enhanced. Developing digital innovation involves acting in a heterogeneous ecosystem (Selander et al., 2010). Companies that want to succeed in the digital sphere must not only identify relevant partners, but also generate new contractual models for the flow of components, information, value, and product liability. One employee said the following.

*"We miss knowledge on every digital technology. We, therefore, collaborate intensively with external partners and develop digital innovations together with them. I think we generate much greater business opportunities when we collaborate beyond traditional customer and supplier relationships."*

Based on the qualitative results, we extended the set of micro-foundations by an additional sixth factor, which we called, '*overcoming digital innovation resistance*.' We learned that the complexity of digital innovation raises resistance at different levels in a company's ecosystem. Constructive opposition is a source of innovative ideas (Adomako et al., 2019; Markham, 2000) that can increase innovation quality by broadening the knowledge base for innovation development (Hauschildt, 2010; Juntunen et al., 2019). Collaborating with skeptical employees, customers, and suppliers also builds trust, and increases the acceptance and implementation of digital innovation. However, the success of digital innovation relies on overcoming resistance, which can take many forms, such as employees lacking the necessary knowledge or willingness to develop digital innovations, job insecurity, legal barriers, internal bureaucracy, and fear of missing customer acceptance. This is in line with past research, which proposes that digital innovation faces numerous barriers, including lack of innovation culture, leadership buy-in, and technological skills, budget restrictions, legal boundaries, limited understanding of urgency, and a focus on daily business (Gfrerer et al., 2021). These facets also mirror prior research that emphasized the relevance of knowledge of digital technologies and the willingness to engage in digital environments (Nauhaus et al., 2021). One respondent summarized as follows:

*"We see a lot of barriers in the development of digital innovations. [...] We have to work with employees who are afraid of losing their workplace. However, we have to cope with these barriers because we have to change our business model."*

Following an exploratory approach, we generated a set of 38 initial items for the six foundations of digital innovation capability. Thereby, the items drew on two sources: (i) the description of the micro-foundations resulting from the conceptual synthesis of the (mainly conceptual) literature, and (ii) the qualitative research. Therefore, the subcategories identified in the qualitative research and conceptual synthesis were used to formulate specific items. We ensured that the items capture the conceptual domain specified in the conceptual part as well as validated in the qualitative research. The items were furthermore pre-tested with three interviewees to ensure that they were uniformly and clearly understood, which resulted in only minor changes in wording. The final set of items is listed in Table 4.

**Table 4**  
Constructs and initial items.

Digital focus
I1: We have recognized the importance of digital innovation for our company.
I2: We have very ambitious digitization goals.
I3: We have formulated and communicated a digital strategy as a guide to develop digital innovation.
I4: We have defined roles, responsibilities and decision-making processes for the implementation of the digital strategy.
I5: Management acts as a role model for digital innovation.
I6: We provide extensive financial resources to implement our digital strategy.
I7: We build new capabilities to implement our digital strategy.
I8: We hire new employees to implement our digital strategy.
I9: We refine our technical infrastructure to implement our digital strategy.
I10: We modify our processes to implement our digital strategy.
Digital innovation process
I11: We consider the innovation possibilities of digital innovation resulting from the combination of hardware and software in our innovation process.
I12: We consider the ongoing potential of digital innovations, for example, because of software updates, in our innovation process.
I13: We consider new business opportunities beyond the primary intended use (e.g., extended data use) of digital innovations in our innovation process.
I14: We are aware that external and unknown market partners may take business opportunities from our digital innovations.
I15: We take precautions to protect our digital innovations against competitors.
I16: We use agile methods and tools (e.g., SCRUM, digital mock-ups) to develop digital innovations.
Digital mindset
I17: In our company, digital innovation is established (e.g., information campaigns, events).
I18: Our employees understand the possible impact of digital innovation on their daily work.
I19: Our employees ask for the implementation of digital innovations.
I20: Our employees discuss the impact of digital innovation on the company in teams.
I21: A high number of our employees are digital natives.
Digital innovation network
I22: We are more dependent on external partners in the development of digital innovation than in the development of other kinds of innovation.
I23: We collaborate with new external partners in the development of digital innovation.
I24: Relationships with external partners have more of a partnership character than a customer-supplier-character.
I25: There is no company in our digital innovation network (neither ourselves nor an external partner) that controls the innovation process.
Digital technology and data management
I26: We are able to identify valuable data (e.g., machine data, user data, etc.).
I27: We are able to identify key digital technologies (e.g., cloud solutions, machine learning, etc.).
I28: We have the appropriate technical systems to store, evaluate and analyze data that is valuable to us.
I29: We are able to generate and merge data from different sources.
I30: We are able to gain knowledge from this data.
I31: We have clear responsibilities for all operational activities relating to data storage, evaluation and analysis.
I32: We coordinate all operational activities relating to data storage, evaluation and analysis across functional and departmental boundaries.
I33: We consider the impact of all operational decisions on data storage, evaluation and analysis.
Overcoming digital innovation resistance
I34: Our employees do not have the competences to develop digital innovations.
I35: Our employees are not willing to develop digital innovations.
I36: Our employees perceive legal conditions (e.g., data protection laws) as barriers to develop digital innovation.
I37: Our employees think that missing customer and supplier acceptance is a barrier to develop digital innovation.
I38: Our internal processes and high levels of bureaucracy are barriers to develop digital innovation.

## 3.2. Study 2: quantitative scale validation

### 3.2.1. Procedure and samples

The validity and reliability of the developed items and constructs were tested, using quantitative data from a cross-sectional industry sample of German and Chilean companies. To fit the purpose of our study, we collected data from companies that had been established for at least three years, excluded subsidiaries without R&D departments (e.g.,

sales offices), pure software companies, and companies with <25 employees, since such organizations tend to lack formal organizational controls. We collected data from companies in various industries to test our measurement instrument between 2019 and 2022. The distribution among different industries from two geographical regions aimed to develop a measurement instrument that can be applied independent of the regional context, which requires assessment if the items and ratings do not systematically differ by region (e.g., due to differences regarding culture, infrastructure, economic development state, language, and interpretation) (Steenkamp and Baumgartner, 1998). We used a five-point Likert scale (ranging from “do not agree at all” to “completely agree”) for all developed items. We contacted senior managers and informed them of the purpose of the study in considering various aspects of innovation management, which additionally included new items on digital innovation capabilities. The companies nominated a set of employees, who regularly worked on innovation tasks, as study participants. Subsequently, they received an individual link to an online survey that included the items to be assessed. A total of 417 employees from 59 product-centric companies participated in the study. Due to missing values in the core constructs, 23 cases were removed, resulting in 394 cases for further analysis.

We split the entire sample into three subsamples, because scale purification, structural validity, and convergent validity assessments should not be performed using the same dataset. The initial scale purification was performed using exploratory factor analysis (EFA), for which the literature recommends a minimum case-to-item ratio of 5:1 (Hair et al., 2009). To meet this recommendation and given our 38 items, we randomly assigned 193 cases from the German sample to the first subsample for scale purification. Structural validity is typically assessed using confirmatory factor analysis (CFA), for which a sample size of >200 cases is recommended (Boomsma and Hoogland, 2001). Therefore, we used the full German sample ( $N = 271$ ) to meet this requirement. For the final convergent validity assessment, we added data collected in Chile ( $n = 123$ ) to the final CFA, which was also used to assess structural invariance. The latter requires multi-group modeling, for which at least 100 cases per group are recommended (Kline, 2005). We acknowledge that this subsampling approach with partial case overlaps represents a compromise to the ideal solution of performing each step with independent samples; however, given the amount of data we were able to collect, we believe that to meet the requirements of the applied statistical methods, this approach is justified in the context of scale development. Table 5 summarizes the characteristics of the subsamples.

### 3.2.2. Scale purification

EFA allows us to determine how well the observed items reflect the underlying psychological concepts of interest. Drawing on Subsample 1 ( $n = 193$ ), we performed a series of EFAs (principal components and varimax rotation). The initial EFA extracted eight factors with eigenvalues greater than one, accounting for 66.1 % of the observed variance. The initial item pool of 38 was reduced to 32 after eliminating 6 items with cross-loadings (cutoff point of 0.33) or low loadings (lower than 0.50). Before interpreting the results, we assessed the data's suitability for structure detection with the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity, which were both supported ( $KMO = 0.89$ ;  $\chi^2(595) = 2603.10$ ,  $p < .001$ ). Furthermore, all communality scores of the items were clearly above 0.50, thereby, at satisfactory levels (Child, 2006). The final solution resulted in seven factors with eigenvalues greater than one and an explained variance of 66.9 %. All items loaded on the factor were originally designed for measurement. The only difference between the intended and empirical factor structures was with respect to the micro-foundation of *digital technology and data management*, for which two separate factors were extracted, i.e., *digital technology capabilities* and *data management*. All factors showed appropriate levels of reliability, as demonstrated by Cronbach's alpha scores ranging from 0.72 to 0.91 (Nunnally and



**Table 5**  
Sample characteristics.

	Subsample 1		Subsample 2			Subsample 3		
	Number		Number		ΔS1	Number		ΔS2
Total number of informants	193		271		78	394		0
Informants Germany	193		271		78	271		0
Informants Chile	0		0		0	123		123
Job areas (informants)	Number	Percentage	Number	Percentage	ΔS1	Number	Percentage	ΔS2
Leadership/Strategy	15	7.8 %	18	6.6 %	3	42	10.7 %	24
Marketing/Sales/Service/Consulting	49	25.4 %	74	27.3 %	25	97	24.6 %	23
R&D/Innovation management	23	11.9 %	37	13.7 %	14	59	15.0 %	22
Production/maintenance	25	13.0 %	33	12.2 %	8	47	11.9 %	14
Product/Project management	26	13.5 %	35	12.9 %	9	51	12.9 %	16
Controlling/Logistics/Process management	11	5.7 %	17	6.3 %	6	23	5.8 %	6
Purchasing	2	1.0 %	4	1.5 %	2	8	2.0 %	4
IT	13	6.7 %	15	5.5 %	2	16	4.1 %	1
Others	29	15.0 %	38	14.0 %	9	51	12.9 %	13
Hierarchical position (informants)	Number	Percentage	Number	Percentage	ΔS1	Number	Percentage	ΔS2
Upper management	18	9.3 %	20	7.4 %	2	58	14.7 %	38
Middle management	32	16.6 %	35	12.9 %	3	75	19.0 %	40
Lower management/team leader	56	29.0 %	79	29.2 %	23	98	24.9 %	19
Employee	87	45.1 %	137	50.6 %	50	163	41.4 %	26
Industry	Number	Percentage	Number	Percentage	ΔS1	Number	Percentage	ΔS2
Manufacturing goods (chemicals, food, plastics, glass, etc.)	7	19.4 %	7	18.4 %	0	8	13.6 %	1
Industrial engineering (machine construction, plant engineering, etc.)	3	8.3 %	3	7.9 %	0	10	16.9 %	7
Utilities (energy, water, recycling)	11	30.6 %	12	31.6 %	1	14	23.7 %	2
Others	15	41.7 %	16	42.1 %	1	27	45.8 %	11
Company size (revenue; Mio. EUR)	Number	Percentage	Number	Percentage	ΔS1	Number	Percentage	ΔS2
Less than 50 Mio.	12	33.3 %	12	31.6 %	0	24	40.7 %	12
51–250	11	30.6 %	12	31.6 %	1	14	23.7 %	2
251–500	1	2.8 %	1	2.6 %	0	1	1.7 %	0
More than 500 Mio.	9	25.0 %	9	23.7 %	0	12	20.3 %	3
n.a.	3	8.3 %	4	11.1 %	1	8	13.6 %	4
Company size (FTE)	Number	Percentage	Number	Percentage	ΔS1	Number	Percentage	ΔS2
Less than 100 FTE	6	16.7 %	8	21.1 %	2	22	37.3 %	14
101–250	9	25.0 %	9	23.7 %	0	11	18.6 %	2
251–500	7	19.4 %	7	18.4 %	0	8	13.6 %	1
More than 500 FTE	14	38.9 %	14	36.8 %	0	17	28.8 %	3
n.a.	0	0.0 %	0	0.0 %	0	1	1.7 %	1
Total number of companies	36		38		2	59		21
No. informants	Number	Percentage	Number	Percentage		Number	Percentage	
1 informant	6	16.67 %	2	5.26 %		3	5.08 %	
2–3	4	11.1 %	3	7.9 %		10	16.9 %	
4–5	15	41.7 %	16	42.1 %		23	39.0 %	
6–7	4	11.1 %	7	18.4 %		9	15.3 %	
8–9	3	8.3 %	2	5.3 %		2	3.4 %	
More than 10 informants	4	11.1 %	8	21.1 %		12	20.3 %	
Average no. of informants by company	5.36		7.13			6.68		

Bernstein, 1994). We also conducted another EFA at the construct level, which resulted in one factor with all capabilities, except *digital innovation network*, which constituted a separate factor. Table 6 summarizes the EFA results.

### 3.2.3. Structural validity assessment

CFA enables us to assess whether an a priori defined theoretical factor structure is consistent with the empirical data. Therefore, we specified a correlation model with all latent variables and their corresponding items and used the larger subsample 2 ( $n = 271$ ) to perform maximum likelihood estimation (CFA). The multivariate normality test revealed no problematic items. The model fits the data well, as indicated by a  $\chi^2/d.f.$  ratio of 1.82, comparative fit index (CFI) of 0.91, incremental fit index (IFI) of 0.91, and root mean square error of approximation (RMSEA) of 0.053, thereby falling within the recommended boundaries (Hu and Bentler, 1998). The chi-square test was significant ( $\chi^2 = 804.32$ ;  $df = 443$ ;  $p < .001$ ), but this was expected in model situations, when the sample size was above 250, with the number of observable variables exceeding 30, as in this study (Hair et al., 2009). We further found that the average item loadings (standardized) for all constructs were  $>0.63$ , that no individual item loading fell below 0.40, and all loadings were significant at the level of  $p < .001$ , thereby supporting indicator reliability. The average variance extracted (AVE) was

clearly above 0.50 for all but the reversely coded construct, i.e., *overcoming digital innovation resistance* (AVE = 0.41). However, the data demonstrated discriminant validity because the square root of the AVE of each construct was larger than the highest correlation with all other latent variables (Fornell and Larcker, 1981), which also applied to overcoming digital innovation resistance. Table 7 summarizes all the results (CFA Model A).

To further assess whether an alternative factor structure might fit the data better, we estimated the fit of a set of model specifications that collapsed two or more factors into a single factor, and then compared the re-estimated model fit with the original model, using the chi-square difference test (Anderson and Gerbing, 1988). The decision on the factors to be merged, was guided by their relationships so that the factors with the highest correlation were merged first. The procedure was continued until the final one-dimensional model. Table 8 summarizes the results; for all comparisons, the alternative models were significantly worse than the original model. We re-evaluated the internal consistency of the constructs in this larger sample, which was supported by Cronbach's alpha values ranging from 0.72 and 0.90.

### 3.2.4. Convergent validity

The relationship between the developed measure and another theoretically related construct must be examined to establish convergent

**Table 6**  
Results of exploratory factor analysis.

Construct/item	Factor loadings							2nd-order loading
	DIF	DIP	DMI	DIN	DTC	DMA	DIR	
Digital focus (DIF) ( $\alpha = 0.91$ ; Eigenvalue = 4.86; Variance Explained = 15.19 %)								0.64
I1 <sup>a</sup>	(–)	(–)	(–)	(–)	(–)	(–)	(–)	
I2 <sup>a</sup>	(–)	(–)	(–)	(–)	(–)	(–)	(–)	
I3	<b>0.63</b>	0.26	0.20	0.08	0.05	0.21	0.03	
I4	<b>0.64</b>	0.19	0.26	0.12	–0.06	0.33	0.07	
I5	<b>0.57</b>	0.26	0.14	0.06	0.17	0.22	0.27	
I6	<b>0.68</b>	0.08	0.09	0.08	0.33	0.15	0.10	
I7	<b>0.79</b>	0.21	0.11	0.10	0.06	0.10	0.25	
I8	<b>0.67</b>	0.12	0.13	0.13	0.14	0.03	0.23	
I9	<b>0.75</b>	0.18	0.03	0.19	0.24	0.00	0.05	
I10	<b>0.75</b>	0.16	0.11	0.09	0.19	0.09	0.00	
Digital innovation process (DIP) ( $\alpha = 0.86$ ; Eigenvalue = 2.72; Variance Explained = 8.49 %)								0.58
I11	0.33	<b>0.62</b>	0.20	0.09	0.34	–0.01	0.07	
I12	0.31	<b>0.72</b>	0.13	0.15	0.25	–0.01	0.17	
I13	0.32	<b>0.74</b>	0.09	0.12	0.27	0.05	0.09	
I14	0.27	<b>0.69</b>	0.09	0.02	0.07	0.17	–0.14	
I15 <sup>a</sup>	(–)	(–)	(–)	(–)	(–)	(–)	(–)	
I16 <sup>a</sup>	(–)	(–)	(–)	(–)	(–)	(–)	(–)	
Digital mindset (DMI) ( $\alpha = 0.82$ ; Eigenvalue = 2.69; Variance Explained = 8.39 %)								0.80
I17	0.08	0.30	<b>0.59</b>	0.12	0.13	0.16	0.31	
I18	0.30	0.13	<b>0.70</b>	–0.02	0.22	0.04	0.29	
I19	0.16	0.06	<b>0.78</b>	–0.06	0.31	0.05	0.06	
I20	0.17	0.06	<b>0.79</b>	0.07	0.09	0.15	0.02	
I21 <sup>a</sup>	(–)	(–)	(–)	(–)	(–)	(–)	(–)	
Digital innovation network (DIN) ( $\alpha = 0.81$ ; Eigenvalue = 2.50; Variance Explained = 7.82 %)								–0.05
I22	–0.11	–0.02	0.00	<b>0.79</b>	–0.04	–0.01	–0.23	
I23	0.29	0.04	–0.07	<b>0.75</b>	0.15	0.03	0.00	
I24	0.23	0.10	0.08	<b>0.79</b>	0.12	0.09	0.06	
I25	0.16	0.14	0.05	<b>0.70</b>	0.01	0.07	0.08	
Digital technology capability (DTC) ( $\alpha = 0.88$ ; Eigenvalue = 3.57; Variance Explained = 11.17 %)								0.76
I26	0.17	0.06	0.14	0.12	<b>0.69</b>	0.04	0.12	
I27	0.22	0.31	0.25	0.09	<b>0.60</b>	0.07	0.21	
I28	0.18	0.15	0.12	0.01	<b>0.74</b>	0.28	0.15	
I29	0.11	0.17	0.16	0.03	<b>0.81</b>	0.20	0.14	
I30	0.17	0.20	0.12	0.05	<b>0.72</b>	0.28	0.11	
Data management (DMA) ( $\alpha = 0.89$ ; Eigenvalue = 2.65; Variance Explained = 8.29 %)								0.58
I31	0.17	0.03	0.02	0.06	0.22	<b>0.87</b>	0.11	
I32	0.20	0.05	0.07	0.11	0.24	<b>0.83</b>	0.04	
I33	0.19	0.10	0.25	0.00	0.20	<b>0.76</b>	0.05	
Overcoming digital innovation resistance (DIR) ( $\alpha = 0.72$ ; Eigenvalue = 2.40; Variance Explained = 7.50 %)								–0.78
I34	–0.14	–0.14	–0.25	0.07	–0.28	–0.20	<b>–0.60</b>	
I35	–0.02	–0.26	–0.28	0.03	–0.01	–0.12	<b>–0.66</b>	
I36	–0.16	0.21	–0.04	0.08	–0.18	0.14	<b>–0.69</b>	
I37 <sup>a</sup>	(–)	(–)	(–)	(–)	(–)	(–)	(–)	
I38	–0.27	0.00	0.00	–0.06	–0.19	–0.12	<b>–0.70</b>	

n = 193.

Bold shows the factor loadings of the items on the construct that they are built of, while the not-bold shows the factor loadings on the other constructs.

<sup>a</sup> Eliminated during scale purification due to low loading or cross-loadings;  $\alpha$ , Cronbach's alpha.

validity. Evidence of such a relationship (e.g., a significant correlation) supports the idea that the new measurement concept identifies meaningful differences. Therefore, researchers are encouraged to include other measures when collecting data for scale validation, that can then be used to assess convergent validity (Hinkin, 1998). We implemented this approach by including a measure of digital innovation success in the questionnaire. We assumed that digital innovation capability and its underlying micro-foundations result in higher innovation success. Thus, we calculated the correlation between digital innovation capability and digital innovation success. Using established scales from past research to measure the economic success of innovation activities (Griffin and Page, 1993; Manion and Cherion, 2009), we changed the measure slightly to match digital innovation. In particular, the survey items asked about the current contributions of digital innovations in increasing revenue, profitability, market share, market creation, image, customer satisfaction, improved product/service quality, and process efficiency

(Cronbach's alpha: 0.95).

In this step, we drew on subsample 3 ( $n = 394$ ), which includes the full dataset collected in Germany and Chile. Before calculating the correlations, we conducted the original CFA to assess the measurement model. Table 7 summarizes the results (CFA Model B). With a larger sample size, the global fit of the model improved ( $\chi^2 = 932.48$ ;  $df = 443$ ;  $\chi^2/d.f. = 2.11$ ;  $p < .001$ ; CFI = 0.93; IFI = 0.93; RMSEA = 0.052). At the indicator level, all factor loadings are significant ( $>0.50$  and significant). At the latent variable level, the AVE of all variables was  $>0.50$ , except for overcoming digital innovation resistance, but its AVE also increased to 0.46 in the larger dataset. Each square root of the AVE demonstrated discriminant validity being greater than the highest correlation with all other variables (Fornell and Larcker, 1981).

In addition to the scores for the seven constructs, we calculated the overall digital innovation capability score for the correlation analysis. To overcome digital innovation resistance, which is reverse-coded, we

**Table 7**  
Results of confirmatory factor analyses.<sup>a</sup>

	CFA Model A			CFA Model B				
Construct/item	Loading		AVE	α	Loading		AVE	α
Digital focus			0.54	0.90			0.59	0.92
I3	0.68	***			0.68	***		
I4	0.71	***			0.75	***		
I5	0.69	***			0.77	***		
I6	0.75	***			0.79	***		
I7	0.82	***			0.85	***		
I8	0.68	***			0.71	***		
I9	0.78	***			0.80	***		
I10	0.74	***			0.77	***		
Digital innovation process			0.63	0.86			0.70	0.91
I11	0.82	***			0.86	***		
I12	0.87	***			0.90	***		
I13	0.83	***			0.86	***		
I14	0.61	***			0.71	***		
Digital mindset			0.57	0.84			0.64	0.87
I17	0.70	***			0.75	***		
I18	0.85	***			0.85	***		
I19	0.76	***			0.82	***		
I20	0.70	***			0.78	***		
Digital innovation network			0.50	0.81			0.57	0.85
I22	0.56	***			0.66	***		
I23	0.78	***			0.85	***		
I24	0.82	***			0.83	***		
I25	0.62	***			0.68	***		
Digital technology capability			0.58	0.87			0.62	0.89
I26	0.64	***			0.70	***		
I27	0.72	***			0.69	***		
I28	0.82	***			0.80	***		
I29	0.82	***			0.87	***		
I30	0.78	***			0.85	***		
Data management			0.73	0.89			0.73	0.91
I31	0.87	***			0.89	***		
I32	0.91	***			0.92	***		
I33	0.77	***			0.81	***		
Overcoming digital innovation resistance			0.41	0.72			0.46	0.77
I34	0.79	***			0.76	***		
I35	0.65	***			0.68	***		
I36	0.47	***			0.58	***		
I38	0.61	***			0.68	***		
χ <sup>2</sup> (df)	804.32		(443)		932.48		(443)	
χ <sup>2</sup> /df	1.82	***			2.11	***		
CFI	0.91				0.93			
IFI	0.91				0.93			
RMSEA	0.053				0.052			
n	271				394			

<sup>a</sup> AVE, average variance extracted.  $\alpha$ , Cronbach's alpha.

\*\*\*  $p < .001$  (two-tailed).

used the inverted construct score to calculate the overall digital innovation capability score. Table 9 summarizes the results of the subsequent bivariate correlation analysis (Pearson). Following Cohen's judgement that correlations should be interpreted as small, moderate, and large when the correlation coefficients are  $>0.10$ ,  $0.30$ , and  $0.50$  (Cohen, 1992), assessing the relationship between the overall concept of digital innovation capability and digital innovation performance provides support for convergent validity, with  $r = 0.51$  ( $p < .001$ ). At the level of the seven micro-foundations, correlations can also be considered moderate to strong, except for the dimension of *digital innovation network*, which does not correlate with performance. However, the dimension was significantly correlated with the other dimensions of the overall concept, suggesting that digital innovation networks relate to the concept of digital innovation capability. Hence, the relevance of having external digitalization partners for achieving performance is a more complex relationship. Taken together, these results support the convergent validity of the new scale.

### 3.2.5. Measurement invariance and within-group consensus assessment

Subsample 3 ( $n = 394$ ) includes cases from two countries, allowing

us to assess the psychometric equivalence of the digital innovation capability scale across countries. Following the common approach to assess measurement invariance (Putnick and Bornstein, 2016), we applied multi-group CFA with various levels of model constraints, across the two countries. Table 10 summarizes the results. The first model tested configural invariance; that is, the items exhibited the same pattern of salient and non-salient loadings across countries. We estimated a nested model using two groups without constraints. Configural invariance was supported by a good model fit ( $\chi^2 = 1615.85$ ,  $df = 886$ ,  $\chi^2/d.f. = 1.82$ ;  $p < .001$ ; CFI = 0.90; RMSEA = 0.045), with all loadings significant at  $>0.40$ . Next, we assessed metric invariance—the equivalence of item loadings on the factors—by constraining the loadings to be equal across groups and comparing the model fit with the configural invariance model (Chen, 2007). The overall model fit was not significantly worse ( $\Delta\chi^2 = 35.74$ ;  $\Delta df = 25$ ;  $p = .08$ ;  $\Delta CFI = 0.00$ ;  $\Delta RMSEA = -0.001$ ), which supports full metric invariance. To assess scalar invariance, that is, whether the mean differences in the latent constructs captured all mean differences in the items' shared variance, we constrained item intercepts to be equal across the two groups, and the overall model fit was then compared with the metric invariance model.

**Table 8**

Results of confirmatory factor analysis – Model fit of dimension variations.

Model	Model fit							
	$\chi^2$	df	$\chi^2/\text{df}$	IFI	CFI	RMSEA	$\Delta\chi^2$	$\Delta\text{df}$
7 dimensions (original)	804.32	443	1.816	0.91	0.91	0.053		
6 dimensions (merged DIF + DIP)	1018.17	449	2.268	0.86	0.85	0.066	213.84	*** 6
6 dimensions (merged DTC + DMI)	1088.49	449	2.424	0.84	0.84	0.070	284.17	*** 6
6 dimensions (merged DMA + DTC)	1060.45	449	2.362	0.85	0.84	0.068	256.13	*** 6
6 dimensions (merged DIR + DMI)	906.85	449	2.020	0.88	0.88	0.059	102.53	*** 6
5 dimensions (merged DIF + DIP + DMI)	1306.53	454	2.878	0.79	0.78	0.080	502.21	*** 11
5 dimensions (merged DTC + DMI + DIP)	1287.81	454	2.837	0.79	0.79	0.079	483.49	*** 11
5 dimensions (merged DMA + DTC + DIP)	1297.35	454	2.858	0.79	0.78	0.080	493.03	*** 11
5 dimensions (merged DIR + DMI + DIR)	1198.23	454	2.639	0.81	0.81	0.075	393.91	*** 11
4 dimensions (merged DIF + DIP + DMI + DMA)	1643.75	458	3.589	0.70	0.70	0.094	839.43	*** 15
4 dimensions (merged DTC + DMI + DIP + DIF)	1608.11	458	3.511	0.71	0.70	0.093	803.79	*** 15
4 dimensions (merged DMA + DTC + DIP + DIR)	1449.43	458	3.165	0.75	0.75	0.086	645.11	*** 15
4 dimensions (merged DIR + DMI + DIR + DIF)	1560.85	458	3.408	0.72	0.72	0.091	756.53	*** 15
2 dimensions (merged DIF + DIP + DMI + DMA + DTC + DIN)	2081.07	463	4.495	0.59	0.58	0.109	1276.75	*** 20
2 dimensions (merged DIF + DIP + DMI + DMA + DTC + DIR)	2003.39	463	4.327	0.61	0.60	0.107	1199.07	*** 20
1 dimension (merged DIF + DIP + DMI + DIN + DTC + DMA + DIR)	2186.44	464	4.712	0.56	0.56	0.113	1382.12	*** 21

DIF, Digital Focus; DIP, Digital Innovation Process; DMI, Digital Mindset; DIN, Digital Innovation Network; DTC, Digital Technology Capability; DMA, Data Management; DIR Overcoming Digital Innovation Resistance. CFI, comparative fit index; IFI, incremental fit index; RMSEA, root-mean-square error of approximation.  $n = 193$ .

\*\*\*  $p < .001$  (two-tailed).

**Table 9**Mean, standard deviations, and correlation matrix.<sup>a</sup>

	Mean	SD	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	ICC (1,k)
1. Country dummy (0 = GER))	0.30	0.46	(–)										(–)
2. Digital focus	3.00	0.97	–0.14**	(0.92)									0.68
3. Digital innovation process	3.02	1.00	–0.15**	0.65***	(0.91)								0.58
4. Digital mindset	2.80	0.95	–0.07	0.53***	0.56***	(0.87)							0.71
5. Digital technology capability	3.34	0.92	0.14**	0.41***	0.50***	0.42***	(0.89)						0.71
6. Data management	2.86	1.07	0.05	0.41***	0.39***	0.36***	0.61***	(0.91)					0.55
7. Overcoming digital innovation resistance	2.86	0.91	–0.33***	–0.12*	–0.02	–0.22***	–0.30***	–0.16**	(0.77)				0.72
8. Digital Innovation Network	3.27	0.92	–0.31***	0.44***	0.42***	0.28***	0.12*	0.08	0.22***	(0.85)			0.57
9. Digital innovation capability	3.06	0.64	–0.02	0.78***	0.78***	0.74***	0.75***	0.68***	–0.38***	0.47***	(–)		0.59
10. Digital innovation success	3.10	1.00	0.27***	0.40***	0.42***	0.49***	0.43***	0.34***	–0.17**	0.06	0.51***	(0.95)	0.62

$n = 394$ .

<sup>a</sup> S.D., standard deviation. Cronbach's alpha reported along the diagonal. ICC(1,k) intra-class correlation coefficient.

\*  $p < .05$ .

\*\*  $p < .01$ .

\*\*\*  $p < .001$  (two-tailed).

**Table 10**

Results of measurement invariance tests.

Model	Model fit							$\Delta\text{CFI}$	$\Delta\text{RMSEA}$
	$\chi^2$	df	$\chi^2/\text{df}$	CFI	RMSEA	$\Delta\chi^2$	$\Delta\text{df}$		
Configural invariance	1615.84	886	1.824	0.90	0.045				
Metric invariance	1651.57	911	1.813	0.90	0.044	35.74	25	0.00	–0.001
Scalar invariance	1817.36	943	1.927	0.88	0.047	165.78	32	–0.02	0.003

$n = 394$  (Germany:  $n = 271$ ; Chile:  $n = 123$ ).

\*\*\*  $p < .001$  (two-tailed).

The significant chi-square difference test ( $\Delta\chi^2 = 165.78$ ;  $\Delta\text{df} = 32$ ;  $p < .001$ ) indicated a worse model fit, but the higher sensitivity of the chi-square difference test in larger samples needs to be considered. The changes in the other fit indices presented mixed results (CFI = 0.02; RMSEA = 0.003). This indicates that means across countries should be compared with caution because of the potential additive bias (Meredith,

1993).

Thus far, we have analyzed the validity of our measurement instrument to capture respondents' individual perceptions in their assessment of their organization's digital innovation capability. However, this measure is intended to support organization-level research. Therefore, a reliable measurement instrument must demonstrate its ability to



produce a similar assessment of an organization, independent of the employee providing the rating. Employees' ratings within a company might vary slightly because of differences in their exposure to organizational practices and activities, depending on their function or hierarchical position. Nevertheless, a reliable measure of a company's digital innovation capability must demonstrate appropriate within-group consensus. Our multi-respondent sample was suitable for this investigation. In particular, we drew on Subsample 3 ( $n = 394$ , organizational level:  $n = 59$ ) to calculate the intra-class correlation coefficients (ICC 1, k), which indicate inter-rater reliability and agreement (LeBreton and Senter, 2008; Shrout and Fleiss, 1979). We report the ICC (1,k) for each subdimension and the overall score for digital innovation capability in Table 9. The ICC (1,k) values ranged between 0.55 and 0.71, confirming levels of agreement that can be interpreted as good to excellent (Fleiss, 1986). This supports the idea that the items allow for a reliable application of the scale to assess the organizational characteristics of digital innovation capability based on individual employees' perceptions.

#### 4. Discussion

When seeking digital innovation, companies must mobilize and deploy capabilities suitable for a specific task (Svahn et al., 2017b). However, digital innovation also requires them to constantly reconfigure their resources, processes, and structures, to take advantage of new opportunities, and sustain a competitive advantage in the dynamic environment of emerging digital technologies. This study conceptualizes and empirically validates a multi-dimensional measure to capture the digital innovation capability necessary for established product-centric companies to successfully shape their business into the digital space. Therefore, we draw on the dynamic capability view (Teece, 2007), and prior literature on organizational factors fostering digital innovation, to identify the relevant micro-foundations necessary for established companies to sense, seize, and reconfigure digital innovation.

The results reveal seven micro-foundations of digital innovation capability, i.e., digital focus, digital innovation process, digital mindset, digital innovation network, digital technology capability, data management, and overcoming digital innovation resistance. Based on a multi-stage empirical design consisting of literature review, qualitative analysis and quantitative validation, we develop and validate a measurement instrument to determine the status quo of organizational capabilities for digital innovation. The results suggest that the measurement instrument covers the relevant dimensions of digital innovation capabilities and is applicable across different industries, employee groups, and countries. Consequently, a valid measurement instrument is available that allows practitioners and researchers to determine the digital innovation capabilities of firms. The strength of our measurement instrument lies in its ability to map the multidimensionality of digital innovation capabilities. Nevertheless, it is possible to use individual constructs separately.

##### 4.1. Theoretical implications

By analyzing the challenges of established product-centric companies, and the capability necessary to enter and grow through digital innovation, we respond to the call for research on how organizations with no experience in using digital technologies should organize for digital innovation (Kohli and Melville, 2018; Menz et al., 2021; Dąbrowska et al., 2022; Williams et al., 2022). We contribute to the literature by introducing a dynamic capability view of digital innovation, as this theoretical foundation addresses the need for transformation and reconfiguration required by companies to engage in digital innovation. By synthesizing prior (mainly conceptual) research on organizational-level antecedents of digital innovation and transformation through the lens of the dynamic capability view, we conceptualize a set of micro-foundations, addressing the specific nature and challenges of digital innovation (Yoo et al., 2012), that should enable established companies

to succeed in digital innovation. As such, our conceptualization complements prior research focused on isolated aspects, such as digital innovation management (Füller et al., 2022; Nambisan et al., 2017), strategy (Kindermann et al., 2020), or competing concerns inhibiting digital innovations (Svahn et al., 2017a). Our approach is also distinct from past frameworks, suggesting sets of resources and capabilities to master digitalization and digital innovation (e.g., Gfrerer et al., 2021; Annarelli et al., 2021; Dąbrowska et al., 2022). In addition to focusing on the organizational factors that enable established companies to reconfigure for digital innovation, we develop a measurement instrument that is empirically tested through qualitative and quantitative research. This study provides a reliable and valid scale to support future research on the antecedents of digital innovation success in the context of established product-centric companies.

##### 4.2. Managerial implications

Based on prior literature, we developed a multi-dimensional measurement instrument to capture digital innovation capability and validated it through qualitative and quantitative research. The items are easy to understand, the survey could be completed expeditiously, and the analysis in the form of aggregate scores is simple. This measurement concept offers companies and their managers the opportunity to reflect on their digital innovation capabilities. When including employees in different functional departments, entities, or hierarchical levels, detected differences in their evaluations can trigger discussions if subgroups only differ in their perceptions or require specific capacity-building measures. A consensus on underperformance with respect to certain micro-foundations can help managers prioritize digital innovation-related interventions at the organizational level; this includes the formulation of a digital innovation strategy when scoring low in this area. The measurement instrument may also allow for a comparison between companies or a benchmarking, which helps identify best practices, and track changes, in digital innovation capability over time. These insights may also help policy makers evaluate the status quo of the industries' digital innovation capabilities. Consequently, policy makers could develop specific education and funding programs to further guide the digital transformation and the building of digital innovation capabilities.

##### 4.3. Limitations and future research

We used a mixed-method approach to develop and validate our digital innovation capability measures. Thereby, analyzing the relationship between digital innovation capability and company success might be important to underline the relevance of the digital innovation capability. For example, future research should investigate the influence of digital innovation capability on digital innovation success and company-level outcomes, such as innovation program performance. Although we already included an analysis that correlates the micro-foundations with digital innovation success (see Table 9), regression models using different performance evaluation datasets should be applied. In this context, future research could also apply designs where dependent and independent variables come from different informants, thereby avoiding common method bias concerns (Globocnik et al., 2022; Kroh et al., 2018).

Further, the performance relevance of digital innovation capabilities may depend on company-level contingency factors. For instance, future research might investigate whether the relevance of certain micro-foundations might differ for companies in high-vs. low-tech industries, high vs. low degrees of servitization, high vs. low risk aversion cultures, or by type of digital technology (AI, IoT, mobile, etc.). This would allow us to learn more about the relative importance of certain micro-foundations in different organizational contexts.

The quantitative study supports the validity of the measurement instrument across regions by collecting data from Germany and Chile.

These two countries differ in terms of culture, industry structure, and digital innovation experience. Despite the generally high influence of the national context on response patterns in surveys (de Jong et al., 2008), we demonstrate the suitability of the measurement instrument for capturing the micro-foundations of digital innovation capabilities in different countries. This is remarkable, given that the questionnaires were completed in the respective local languages. However, our evaluations also showed limited scalar invariance; that is, the intercepts varied systematically by region. Future research that presents group-mean comparisons across countries should evaluate this bias. In the case of invariance violations, several remedial strategies enable meaningful mean comparisons. For instance, intercept restrictions can be relaxed, and if less than half of the scale items are not invariant, past research has shown that the latent mean comparison results are still valid (Steinmetz, 2013). In large-scale studies with many subgroups, correction approaches, such as alignment-within-CFA (Marsh et al., 2018), can be applied.

Finally, our research designs were applied at only one point in time for each company. However, building digitalization capabilities is a long-term process (Büschgens et al., 2013). Future longitudinal studies must further investigate the extent to which the measurement reflects changes in digital innovation capability over time. The evidence presented in validating the scales and high inter-rater reliability is optimistic; however, it is possible that the effect of fundamental company characteristics on the response pattern are so strong that changes in digital innovation capability are limited in their visibility.

#### CRediT authorship contribution statement

**Julia Kroh:** Investigation, Methodology, Formal analysis, Writing – original draft. **Dietfried Globocnik:** Methodology, Formal analysis, Writing – review & editing. **Carsten Schultz:** Conceptualization, Writing – review & editing, Supervision. **Frederike Holdhof:** Conceptualization, Investigation. **Søren Salomo:** Conceptualization, Writing – review & editing, Supervision.

#### Declaration of competing interest

During the preparation of the work “MICRO-FOUNDATIONS OF DIGITAL INNOVATION CAPABILITY – A MIXED METHOD APPROACH TO DEVELOP AND VALIDATE A MULTI-DIMENSIONAL MEASUREMENT INSTRUMENT” the authors Julia Kroh, Dietfried Globocnik, Carsten Schultz, Frederike Holdhof, and Søren Salomo did not use any AI and AI-assisted tools or services.

#### Data availability

Data will be made available on request.

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#### Appendix 1. Interview guideline

##### Part (A) Digital innovation in theory

- What is your understanding of digital innovations? Please define digital innovation.
  - Based on the definition of digital innovations, what might be the most important requirements for digital innovation development?
- Part (B) Digital innovation management

How do you develop digital innovations? Please describe the digital innovation process from ideation to digital product's / service's market

introduction and give examples.

How does digital innovation development differ from non-digital innovation management?

Please specify with regard to...

... data availability and management.

... competences and mindset.

... strategy and process design.

... collaboration intensity with internal and external stakeholders.

What did you change in your innovation process to considerate digital innovations' requirements?

#### Part (C) Digital business model

How important are digital innovations for your firm?

How do digital innovations influence your current and future business model?

Which value do you generate from digital innovations today?

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**Dr. Julia Kroh** is a postdoctoral researcher at the Chair of Technology Management at the Institute for Innovation Research at Kiel University, Germany. Her research focuses on stakeholder management in complex innovation processes. Her research fields comprise the management of complex innovation processes like digital innovation, service innovation, and urban innovation. Her work was already published in the *Journal of Product Innovation Management* and *Technological Forecasting and Social Change*.

**PD Dr. Dietfried Globocnik** works as senior scientist at the University of Klagenfurt and the University of Graz. He holds a doctorate in social and economic sciences from the University of Graz and a habilitation in business administration from the University of Klagenfurt. His research interest entails innovation marketing, corporate entrepreneurship and organizing innovation activities in MNEs. His academic work is published in books and journals such as *Journal of Product Innovation Management*, *Technovation* and *European Management Journal*.

**Prof. Dr. Carsten Schultz** is a professor for Technology Management at the Institute for Innovation Research at Kiel University, Germany. He received his doctorate from Berlin University of Technology. His research concentrates on innovation and network management with on focus digital services. Further research interests include the management of radical innovations and university–industry collaborations. He has published several articles in academic journals as well as a number of books including a widely used textbook on innovation management.

**Frederike Holdhof** is a PhD student at the Chair of Technology Management at the Institute for Innovation Research at Kiel University, Germany. Her research focuses on digital innovation development in mid-sized and established firms.

**Prof. Dr. Søren Salomo** holds the Chair of Technology and Innovation Management at Technische Universität Berlin. He is also professor for innovation management at the Center for Entrepreneurship at DTU, Copenhagen. He holds a diploma and a doctorate in business administration from Kiel University. His research interests entail corporate innovation management with a special focus on process and organizational system mechanisms for supporting radical innovation. His work is published in journals, such as the *Research Policy*, *Creativity and Innovation, Management*, and *Journal of Product Innovation Management*.