Received: 12 June 2021 | Revised: 13 October 2022 | Accepted: 17 October 2022

DOI: 10.1002/gsj.1469

RESEARCH ARTICLE

GLOBAL STRATEGY JOURNAL WILEY

Digitalization of cross-border R&D alliances: Configurational insights and cognitive digitalization biases

Ricarda B. Bouncken[1] | **Viktor Fredrich**[1] | **Noemi Sinkovics**[2] | **Rudolf R. Sinkovics**[2,3]

[1]Faculty of Law and Economics, Chair of Strategic Management and Organization, University of Bayreuth, Bayreuth, Germany

[2]Adam Smith Business School, University of Glasgow, Glasgow, UK

[3]LUT University, Lappeenranta, Finland

Correspondence
Ricarda B. Bouncken, Faculty of Law and Economics, Chair of Strategic Management and Organization, University of Bayreuth, Prieserstraße 2, 95444 Bayreuth, Germany.
Email: bouncken@uni-bayreuth.de

Abstract

Research Summary: Firms implement digital technology for improving coordination and communication in cross-border R&D alliances. However, there is great ambivalence regarding how digitalization influences cross-border knowledge transfers. Our analysis clarifies some of this ambivalence by providing different configurations of absorptive capacity in cross-border R&D alliances. The fuzzy-set qualitative comparative analysis (fsQCA) reveals only low absorptive capacity achievement in most configurations of digital technology implementation. The findings indicate effects of cognitive digitalization biases, under which firms take the benefits of digital technology for granted while ignoring deep-level challenges rooted in the contextuality of international ties. However, high absorptive capacity is achievable when (1) allying with bigger and younger partners, (2) under technological similarity, and (3) coping with the associated digitalization biases.

Managerial Summary: Firms are eager to grasp the potential of digital technology. Within R&D alliances, digital technology is deemed to facilitate better coordination and communication. However, advantages from digital transformation are not always realized, as firms may overestimate the ease and usability of the underpinning technologies. We find that learning and understanding of partner knowledge is improved when R&D partnerships are forged between bigger and smaller partners, when partners feature technological similarities and both parties are similarly minded regarding technologies and do not take technology advantages for granted.

KEYWORDS

cross-border R&D alliance, cultural distance, technological distance, digital technology, global connectivity

1 | INTRODUCTION

Today, firms continuously implement digital technology vis-à-vis their existing technology properties in their internal operations (Wimelius et al., 2021) and external alliance relationships (Kang & Zaheer, 2018; Nachum & Zaheer, 2005; Zaheer et al., 2012). Digital technology transforms how firms operate, compete, and collaborate (He et al., 2020; Snow et al., 2017; Tilson et al., 2010); it changes how firms recognize, assimilate, transform, and apply knowledge. In this vein, a new theory has emerged in international business (IB) research on "global connectivity" (Autio et al., 2021; Cano-Kollmann et al., 2016; Castellani et al., 2022; Goerzen, 2018; Lorenzen & Mudambi, 2013; Sinkovics et al., 2019). Digital technology also influences connections between firms in their cross-national alliances (Roberts et al., 2012). In particular, R&D alliances require the transfer and use of external knowledge (Kim & Inkpen, 2005; Lane et al., 2001), including tacit knowledge transfer (R. Bouncken & Barwinski, 2021). Yet, as Szulanski (1996) has shown, the knowledge to be transferred between allying firms is subject to a set of limitations related to the knowledge characteristics, the source, the recipient, and the context of the transfer. Digital technology might not always cope with such knowledge "stickiness." In addition, firms implement digital technologies that have different characteristics. Thus, digitalization might ease the transfer of knowledge and contribute toward a "flat world" where global disaggregation of services leverages global resources and mitigates knowledge transfer (Mithas & Whitaker, 2007). Yet, given a potential inability to cope with knowledge stickiness, digitalization might also require a physical presence as a driver of "spikes" in the global economy (Mithas & Whitaker, 2007). Therefore, a firm's digital technology implementation in its R&D alliances will directly influence its absorptive capacity, but the effects are ambiguous (He et al., 2020).

Global connectivity research has shown that the effect of digital technology on absorptive capacity is contingent on geographic distance, and this contingency is most ambivalent in R&D alliances (Kang & Zaheer, 2018; Nachum & Zaheer, 2005; Zaheer et al., 2012). Digital technology can support but also deter a firm's absorptive capacity (Cano-Kollmann et al., 2016; Liao et al., 2007; Nachum & Zaheer, 2005; Nambisan et al., 2017; Setia et al., 2013; Törnroos et al., 2017; Zaheer et al., 2012). On the one hand, digital technology supports communication and the process infrastructure of global R&D connections (Turkina et al., 2016; Turkina & Van Assche, 2018), allowing digitalized operations and virtual person-to-person communication (Forman & van Zeebroeck, 2019). Further, digital technology improves the transferability of objects (Cherbib et al., 2021; Lorenzen et al., 2020). On the other hand, digital technology deters absorptive capacity because it channels more conversational relationships than "handshake" relationships, which are essential for R&D, especially when crossing international borders (Leamer & Storper, 2001). In addition, spatial characteristics of alliance partners' international locations or markets can limit the understanding, use, and implementation of knowledge (Cano-Kollmann et al., 2016; Törnroos et al., 2017). Further, there is high specificity in digital technology (Hanelt et al., 2021), so firms can source and absorb only some knowledge embodied in digital solutions (Forman & van Zeebroeck, 2019) and rarely absorb more integrative knowledge (Liao et al., 2007; Nambisan et al., 2017; Setia et al., 2013).

Considering these ambivalent and context-related influences, we formulate the following research question: *Under which conditions can firms gain absorptive capacity in cross-border R&D alliances when they strongly utilize digital technology?*

Our configurational research approach acknowledges that digital technology use is not per se supportive of absorptive capacity but depends on certain factors being in place or absent simultaneously—a concept referred to as *conjunctural causation* (Misangyi et al., 2017). Regarding the ambivalence, we explore the geographic, cultural, market, and technological distances at the alliance level while combining them with important digitalization-related firm-level demographic characteristics. For researching configurations, we apply fsQCA (Fainshmidt et al., 2020; Verbeke et al., 2019), examining 48 dyadic cross-border R&D alliances. Although our primary focus is on cross-border R&D alliances, we complement the cross-border sample with 144 national R&D alliances (cf. Appendix).

Our findings unexpectedly reveal that all *low* configurations of R&D alliances apply digital technologies while only two (out of four) high-level configurations implement digital technologies. The two high-level paths indicate that cross-border R&D alliances achieve high levels of absorptive capacity through digital technology implementation by (1) selecting bigger and younger partners, and (2) assuring technological similarity. We derive the notion of "digitalization biases," in which firms and their employees working in the R&D alliance tend to underestimate digitalization challenges and overestimate its merits, while not paying sufficient attention to the necessary level of detail and the contextual embeddedness of knowledge. Such detail may include the local context, the fit to the local context, the limitations of knowledge digitalization (i.e., virtuality trap; Yamin & Sinkovics, 2006), the stress digitalization puts on organizations (i.e., technostress; Becker et al., 2020; Maier et al., 2022), false assumptions regarding what digital technology can do (i.e., black-boxing; Anthony, 2021), and the still-lingering demands of personal contact for tacit knowledge transfer.

Our study contributes to the emerging global connectivity literature (R. Bouncken & Barwinski, 2021; Lorenzen et al., 2020; Mudambi et al., 2018; Sinkovics et al., 2019; Tallman et al., 2018). To that theory, we first contribute by identifying essential *causal recipes* (Y. Park et al., 2020), of which technological similarity is most important for digital technology implementation in cross-border R&D alliances. Second, we highlight cognitive digitalization biases related to taking the benefits of digital technology for granted while ignoring the contextuality of culturally bound, locally embedded, and complex knowledge in international ties.

2 | CONCEPTUAL BACKGROUND

2.1 | Digital technology

Digital technology contains diverse information, computing, communication, and connectivity technologies (Bharadwaj et al., 2013; Setia et al., 2013). These are frequently referred to as "advanced technologies" (Sinkovics & Sinkovics, 2020) and go beyond the internet infrastructure technology, as referenced in early IB articles (de la Torre & Moxon, 2001). Such technologies include big data analytics, cloud computing, additive manufacturing, social media, and the internet of things (Nwankpa & Datta, 2017). Digital technology has been changing processes and outcomes to be more programmable, addressable, sensible, communicable, memorable, traceable, and accessible (Yoo et al., 2010). For example, big data can improve firms' understanding of customer needs and problems, and improve the ease and validity of quality checks in manufacturing (H. Chen et al., 2012; Loebbecke & Picot, 2015; Mithas et al., 2012). Digital technologies contribute to digital transformation but are also the object of innovation (Kleis et al., 2012). For example, 3D printing is a technological innovation that enables firms to develop and produce novel and individualized products across different locations and print them where they are needed (R. Bouncken & Barwinski, 2021; Rindfleisch et al., 2017).

Digital innovation can lead to changes in or the elimination of value chain stages while allowing new ventures, new business models, and supporting R&D processes (Tallman et al., 2018; Täuscher et al., 2021). Particularly far-reaching is the implementation of Industry 4.0 solutions, which include digitalized production planning and scheduling, capacity planning, and maintenance but also collecting and processing production data for process efficiency and process innovation. Global and remote steering of operational processes can transform traditional value chains and stimulate the creation of new business models (Horváth & Szabó, 2019). Although developed for production processes, Industry 4.0 also affects the R&D processes of existing systems by providing additional data and novel communication methods. The implementation of Industry 4.0 solutions eases knowledge transfer due to automated exchange processes and allows for control across different geographical locations (Ardito et al., 2021). Hence, Industry 4.0 further enables the global connectivity of R&D.

2.2 | Cross-border R&D alliances as conduits for absorptive capacity

R&D, with its high investments and uncertainties, occurs not only in single firms but also in alliances. R&D alliances characterize inter-firm collaboration for complementarities that support R&D processes for innovation purposes (Cui & O'Connor, 2012; De Luca & Atuahene-Gima, 2007; Delgado et al., 2010; Eriksson, 2011; Kim & Inkpen, 2005). Fundamental to R&D alliances is knowledge transfer and its absorption (Simonin, 1999, 2004). R&D tends to progress when firms source distinctive technologies and knowledge from various locations and local hotspots (Berry, 2014; Cantwell, 1989; Mudambi et al., 2018). Accordingly, firms form R&D alliances locally and across national borders (Kang & Zaheer, 2018). These cross-border R&D alliances allow the combination and absorption of knowledge from different international locations to gain absorptive capacity (Awate et al., 2015; Mudambi et al., 2018; Sinkovics et al., 2019). Absorptive capacity is a common proxy for garnering valuable knowledge and alliance performance, especially when patents or innovative solutions have not (yet) occurred. The *general* absorptive capacity of a firm describes its ability to (1) understand new external knowledge, (2) assimilate it, and (3) apply it to commercial ends (Cohen & Levinthal, 1990, p. 128). The *relative* absorptive capacity of a firm can differ for each of its external knowledge sources, calling for a dyadic level of analysis. Although the *relative* absorptive capacity of a firm in a dyadic R&D alliance is a key outcome in the R&D alliance itself and an important proxy of its performance (Lane et al., 2001; Lane & Lubatkin, 1998), there is little known about how digital technology affects R&D alliances, and especially cross-border R&D alliances (He et al., 2020). Choosing relative absorptive capacity as our key outcome is in line with Szulanski (1996), who identified a recipient's lack of absorptive capacity as the most important origin of information stickiness and a major barrier to knowledge transfer.

3 | RESEARCH MODEL AND CONFIGURATIONAL PATTERN PROPOSITIONS

3.1 | Digital technology and cross-border R&D alliances

Digital technology brings significant changes in global connections and associated R&D processes (Turkina et al., 2016; Turkina & Van Assche, 2018). Digitalization might contribute to a "flat world," where global disaggregation of services leverages global resources and mitigates knowledge transfer barriers, or a "spiky world," where a high concentration of skilled workers in local clusters drives the global economy. Although a net flattening effect of digitalization is likely, there is also some evidence for necessary skills and the need for physical presence as drivers of "spikes" in the global economy (Mithas & Whitaker, 2007).

In this important domain, a new theory has emerged under the umbrella term of "global connectivity" (Autio et al., 2021; Cano-Kollmann et al., 2016; Castellani et al., 2022; Goerzen, 2018; Lorenzen & Mudambi, 2013; Sinkovics et al., 2019). Initially, digital technology was designed to support firms' absorptive capacity (Ardito et al., 2021) and encourage them to replace physical infrastructure with digital alternatives (Ahi et al., 2021). Yet, digital technology also can endanger or complicate the creation of absorptive capacity in cross-border R&D alliances.

Positive effects of digital technology implementation stem from lowering transportation costs in cross-border relations, which become less relevant with greater digitalization (Lorenzen et al., 2020; Tallman et al., 2018). Costs of transportation and knowledge embeddedness have been among the key parameters in decisions about international location (Schotter & Beamish, 2013). Transportation costs greatly affect the manufacturing of physical goods because intermediate goods have to be physically shipped (Castellani et al., 2013). Digital technologies have the potential to eliminate or reduce some of these factors, and can be expected to mask or reinforce other aspects (Pezderka & Sinkovics, 2011). In the context of R&D, which mainly faces challenges from managing knowledge embeddedness, shipping costs are less of a concern, although physical distance may retain its relevance in hindering or facilitating the physical co-location of experts (Cano-Kollmann et al., 2016; Pezderka & Sinkovics, 2011). Still, digital technologies can also support absorptive capacity by transferring digitalized knowledge or allowing virtual person-to-person communication.

However, there are barriers to the absorption of knowledge via digital technology or the knowledge incorporated in digital technology (Kang & Zaheer, 2018; Nachum & Zaheer, 2005; Zaheer et al., 2012), mainly because digital technology may transfer only some knowledge components, involves problems in transferring tacit knowledge, and might only allow conversational exchanges rather than firm "handshakes" (Leamer & Storper, 2001). As shown by Szulanski (1996), the knowledge to be transferred between allying firms is subject to a set of limitations related to the knowledge characteristics, the source, the recipient, and the context of the transfer. Especially, digital technology might not always cope with the stickiness of knowledge, which might require direct personal copresence and socio-emotional sharing. Only under the condition of a shared digital identity have digital technologies been able to transfer tacit knowledge (R. Bouncken & Barwinski, 2021).

In the context of cross-border R&D alliances, other international differences and cultural aspects will limit the transfer via digital technology; for example, due to the spatial characteristics of the two locations in which partners are embedded (Cano-Kollmann et al., 2016; Törnroos et al., 2017). Furthermore, the knowledge incorporated in digital technology might be complex and integrative, restricting easy knowledge transfer (Leamer & Storper, 2001; Liao et al., 2007; Nambisan et al., 2017; Setia et al., 2013). Not all digital technology comprises easily transferable components of programs and technology. Digital technology itself can be very complex, dynamic, and firm-specific. These conditions limit substantial digital technology use for the absorption of knowledge in R&D alliances (Hanelt et al., 2021). The idiosyncratic knowledge attributes of the implicit geographies, markets, technologies, and cultures will create an interdependent complex system of *combinatory effects* on how well digital technologies support knowledge transfer in cross-border R&D alliances (Lanzolla et al., 2021). These conditions are also well reflected by research on perceived and actual distances in R&D alliances (Ambos & Håkanson, 2014; Dow, 2017; Maseland et al., 2018). Existing evidence suggests that to achieve the goals of R&D alliances, firms need the right combination of these *causal recipes*. Causal recipes are formal statements explaining how causally relevant elements combine into configurations associated with an outcome of interest (Y. Park et al., 2020; Yan et al., 2020).

In addition, firm-level characteristics seem to interact with the above conditions (Barnett et al., 2021; Gopalakrishnan & Bierly, 2006). First, firm age directly affects openness toward digital technology. Established firms tend to have greater problems implementing and utilizing digital technology (Lee & Trimi, 2021). Relatively old firms can experience greater levels of technostress, broadly defined as stress related to working with information technologies (Maier et al., 2022). Furthermore, older firms experience virtual media for personal exchanges as more complicated (Reuschl et al., 2022). Additionally, digital technology often requires high investments in technical and human resources (Forman & van Zeebroeck, 2019; Hanelt et al., 2021), which smaller firms might not have and thus search for in their alliance partners.

Second, bigger firms might have greater financial resources, and can also access greater network effects when a greater user base of digital technology progressively increases potential benefits (Loebbecke & Picot, 2015). Hence, bigger firms might better leverage digital technologies in alliances. While there is a danger in allying with a larger and more powerful firm, there is also high potential for garnering growth and technology leverage with such partners. Considering the complementarity argument in alliance research, older and smaller firms might benefit in their absorptive capacity when allying with a bigger and younger partner. We reason that the effects of relative firm size and age on absorptive capacity relate to how well firms can understand the new knowledge of the partner (Rothaermel & Boeker, 2008; Zhang et al., 2021). Greater technology or market overlap will ease the understanding and usage of the partner's knowledge base. In what follows, we argue and propose a set of related idiosyncratic contingencies that pave equifinal causal paths to above-average absorptive capacity of Firm A relative to its R&D alliance partner B in the presence of *alliance-level* digital technology implementation.

3.2 | Global connectivity: Zooming in on configurations

In understanding configurations of firm-centric knowledge absorption from a specific R&D alliance, we follow the concept of causal recipes (Y. Park et al., 2020). Geographic distance will influence R&D alliances as conduits of knowledge transfer. Traveling over greater distances and spending time at the partner firm will not only have cost implications (Catalini et al., 2020), but may also be hampered by several other factors including but not limited to obtaining visas, language barriers, local transportation, water safety, climate issues, health issues, and female travel risk (Lorenzen et al., 2020; Schotter & Beamish, 2013). Toedtling et al. (2012), and similarly Leamer and Storper (2001), propose that geographic proximity is essential in the context of complex knowledge exchange that requires interactive learning and conversations rather than handshake relations. Travel and the cognitive distance among members from different nations reduce the impact of geographic proximity and are often perceived as significant barriers to knowledge transfer in such relationships (Toedtling et al., 2006; Toedtling et al., 2012). In addition, firms might aim to protect their knowledge and competencies, and find this easier across distances because co-location increases the chance of unintended tacit knowledge spillovers (R. Bouncken & Barwinski, 2021; Narula & Santangelo, 2009). Hence, especially when there is low market distance, firms might see high risks of unintended tacit knowledge spillovers in direct physical encounters.

Digital knowledge flows may lower the importance of direct knowledge transfer and the influence of geographic distance (Awate et al., 2015; Mudambi et al., 2018). Yet, these merits depend on how well digital technology can represent or transfer knowledge. Digital knowledge transfer with external partners can be based on or supported by programs, codes, and templates (Forman & van Zeebroeck, 2019). Still, these knowledge elements must be understood by partners. Understanding the underlying knowledge bases will be easier when firms have greater levels of technological similarity. Previous research has shown that technological complementarity will stimulate novelty in R&D alliances (Harrison et al., 2001). Technological complementarity requires a minimum degree of overlap (Chung et al., 2000). If the technological distance between the collaborating firms is too large, this may hurt their ability to understand, assimilate, and apply each other's knowledge (Lin et al., 2012; Srikanth & Puranam, 2011). This effect may be further exacerbated when physical co-location is impossible, or firms attempt to bypass associated costs by predominantly relying on digital technologies (Forman & van Zeebroeck, 2019; Sinkovics et al., 2019). Additionally, past information systems research reveals that digital technology is often complex and specific to a firm. Any technological distance will likely complicate the knowledge absorption processes among firms (Hanelt et al., 2021). Hence, achieving absorptive capacity and overcoming geographic distance demands lower technological distance among firms.

In this setting, digital technologies can facilitate connections even in the absence of co-location, group membership, and prior relationships, thus allowing the sharing of digitalized information, know-how, and personal experience (Ravichandran et al., 2017). Digital knowledge transfer may eliminate the influence of geographic distance (Awate et al., 2015; Mudambi et al., 2018). When technological knowledge or its local embedding is less similar among the exchange parties (Awate et al., 2015) or when the knowledge is complex and tacit, recursive exchanges and social aspects can play a critical role (Martin & Salomon, 2003). These effects might remain critical for digital innovation and may necessitate some physical, even if temporary, co-location as knowledge embeddedness complicates knowledge transfer in distributed and locally dispersed processes. In addition, direct knowledge transfer might be more important and frequent when there is cultural diversity among firms (Pesch & Bouncken, 2018). The digitally enabled knowledge transfer among alliance partners can work even in the context of weak ties and serendipitous exploration of knowledge (Liu & Ravichandran, 2015) when firms share the digital identity of the market or industry (R. Bouncken & Barwinski, 2021). While the technological distance between two firms refers to differences in their knowledge bases (Lin et al., 2012), market distance can be defined as industry-related structural differences between collaborating firms. Yan et al. (2020) find that, to achieve breakthrough innovation, focal firms should strive to collaborate with coopetitors characterized by low market distance and medium technological distance. However, the associated risks are offset when low market distance comes with similar technology and technology-inspired identity (R. Bouncken & Barwinski, 2021). Past coopetition research shows that R&D alliances among firms in the same market can achieve scale and scope advantages for the dyad against outside competitors (Shu et al., 2017). These advantages improve knowledge transfer, understanding, and innovation (Yadav et al., 2022).

Expected configurational pattern proposition 1. *Firms in dyadic cross-border R&D alliances will achieve high levels of absorptive capacity from the focal alliance by implementing digital technologies in configurations of high geographic distance, low technological distance, and low market distance in the dyad.*

Cross-border alliances are typically not only affected by geographic but also by cultural differences (Choi & Contractor, 2016). These differences might have combined effects with technological similarity and digital technology use in R&D alliances. Cultural differences might be measured directly by respondents' cultural profiles or perceived cultural distance between individuals nested in organizations (Pesch & Bouncken, 2017). Dyadic R&D alliances as the unit of analysis consist of different individuals from each firm who are in contact with each other. These individuals come from diverse functional and national backgrounds (R. Bouncken & Kraus, 2014). While the cultural distance among individual members of R&D teams might be blurred, each firm still operates from a specific national background in cross-border R&D alliances (R. B. Bouncken & Winkler, 2010). Accordingly, we now turn to the more macro-level informed measure of cultural distance as defined by Kogut and Singh (1988). Cultural distance in cross-border alliances is the degree to which the cultural norms and practices in one country differ from those in another country (House et al., 2006). Cultural differences may result in different interpretation systems, thus creating a risk of reduced understanding, further adding difficulty to geographic and technological distances in garnering absorptive capacity. However, cultural differences can also be a source of novel ideas originating from different behaviors and cognitive styles (Pesch & Bouncken, 2018). When perceived and acknowledged, cultural distance can be bridged, even in a digital context (Sinkovics et al., 2019).

Further, using the same or similar digital technology can create a certain degree of shared identity among firms. Such shared digital identity can build a socio-emotional connection between actors that may foster knowledge sharing, decoding, and integration (R. Bouncken & Barwinski, 2021). The co-existence of a shared digital identity with an awareness of cultural differences between the two countries can create a fertile ground for building knowledge connectivity and creativity (Sinkovics et al., 2019). Still, the different mindsets of alliance participants influenced by national culture and specific local embedding (Doloreux & Turkina, 2021; Turkina et al., 2016) might intermingle with other factors (Peterson et al., 2018) to complicate the understanding of technology and the bridging of geographic distance via virtual media for the development of the firm's absorptive capacity.

> **Expected configurational pattern proposition 2.** *Cultural distance in dyadic cross-border R&D alliances will act as an inhibitor condition for achieving high levels of absorptive capacity from the focal alliance in configurations that implement digital technologies to bridge a high geographic distance.*

Moreover, firm size, firm age, and cross-cultural issues intermingle with the merits of coopetition among firms in the same market (Gnyawali & Park, 2011; Knein et al., 2020).

Relative firm size and age determine digital technology leverage and firms' relative capacity to understand, assimilate, and integrate each other's knowledge bases, especially in asymmetric "student–teacher" dyads (Lane & Lubatkin, 1998). Older firms tend to be more rigid and restricted by potentially outdated and obsolescent technologies (Rothaermel & Boeker, 2008; Sørensen & Stuart, 2000). Firm size is important considering the high investment costs in digital technology and the network effects related to digital technology (Cennamo, 2021; Chu & Manchanda, 2016). Bigger, and hence more powerful, firms invest in digital technology and reap its network effects (Gregory et al., 2022). Thus, bigger firms in R&D alliances might gain more advantages related to absorptive capacity when they implement digital technology in their R&D alliances. As aforementioned, we propose that the effects of firm size and age on absorptive capacity will hinge on how well collaborating firms can understand the new knowledge, which necessarily depends on technology or market overlap, and whether digital technologies can bridge the geographic and cultural distances.

> **Expected configurational pattern proposition 3.** *Firm size and firm age will influence how well firms in dyadic cross-border R&D alliances will achieve high levels of absorptive capacity from the focal alliance: firms collaborating with younger and bigger partners will specifically benefit in terms of absorptive capacity from the focal alliance when implementing digital technologies in configurations of high geographic distance, low technological distance, and low market distance in the dyad.*

4 | METHODS

4.1 | Analysis

We theorize about the multiplicity of digital technology implementation in alliances and propose a set of causal recipes for achieving relative absorptive capacity using a deductive approach, as recommended by Y. Park et al. (2020). This study follows advances in neo-configurational methods to overcome the limitations of conventional regression-based analysis (Fainshmidt et al., 2020; Misangyi et al., 2017). By applying *fuzzy-set qualitative comparative analysis* with fsQCA 3.1, we focus on *combined effects* of causal conditions instead of independent *net effects* of competing explanatory variables (Ragin, 1987). These causal conditions constitute different sets of characteristics associated with a given outcome. In technical terms, *equifinality* allows for different causal paths leading to the same outcomes, and *causal asymmetry* implies that the presence of a condition associated with the presence of an outcome does not necessarily imply that the absence of said condition is associated with the outcome's absence. In line with established QCA guidelines (Ragin, 2008; Schneider & Wagemann, 2012), we first ran a preliminary necessity analysis to identify consistent single necessary causes. We added a series of post hoc and robustness tests to an extended appendix with plain-text explanations of additional insights.

4.2 | Data sources and sampling

We built our population from eight exhibitor lists of international trade fairs hosted in Germany during 2015–2018. Overall, 42,261 firms from 97 countries participated in these trade fairs (Top3: Germany 29.3%, China 14.7%, USA 6.6%, $\sum$ top10: 74.0%) with a sample-size adjusted diversity score ($Blau_N$) equal to 0.88 (Biemann & Kearney, 2010). We chose these trade fairs to address our research question because they are commonly accepted industry ecosystems of individuals, organizations, markets, societies, and cultures facilitating innovation and collaboration (Sarmento & Simões, 2018). The common theme of these trade fairs is "Industry 4.0," which marks the next phase in the digitalization of the manufacturing sector (Baur & Wee, 2015). The core vision of Industry 4.0 is the interconnected "smart" factory, which allows boundary-free human–machine interactions through the application of digital technologies (Ardanza et al., 2019). These digital technologies can also be applied within inter-organizational alliances (Cherbib et al., 2021).

We, therefore, personally invited over 9000 firm representatives from top and middle management to participate in a survey about their firm's digitalization. Respondents were asked to refer to one specific alliance and disclose the partner's firm name, resulting in a total of 2807 paper-and-pencil or tablet-based questionnaires (raw response rate = 31%) from 63 countries (Top3: Germany 37.8%, China 14.3%, USA 5.1%, $\sum$ top10: 78.1%, $Blau_N = 0.83$). Not all participants indicated an alliance partner (missing: 47%) or were sufficiently knowledgeable to serve as a key informant (minimum set to 4 on three 7-point Likert-type knowledgeability items). We further excluded invalid cases, cases with missing model variables, multi-partner alliances, and all non-R&D alliances. Next, we excluded all cases where *both* firms filed no patents in the period 6 years before and 2 years after the survey (33%). Our final sample consists of 292 dyadic R&D alliances from 44 unique countries (responding Firm A: 33 countries, $Blau_N = 0.74$; partner Firm B: 36 countries, $Blau_N = 0.80$). Of these dyadic R&D alliances, 144 (i.e., 49%) were national and 148 (i.e., 51%) were cross-border alliances.

Despite fsQCA being less sensitive to sampling issues due to the theoretically informed calibration process (Fiss, 2011), we assessed the extent of potential selection biases by estimating the inverse Mills ratio in a binary selection model (Certo et al., 2016) for our final sample of 292 dyadic R&D alliances drawn from the overall population of 42,261 firms. A series of firm characteristics at the firm level (firm size and age), country level (English proficiency index and proportion of individuals of the population using the internet), and trade fair level (geographic distance of exhibitor to trade fair and the number of exhibitors in the hall where the exhibitor is located) significantly predicted the selection ($\chi^2 = 75.00$, df $= 6$, $p < .001$, Nagelkerke-$R^2 = 2.2\%$). We added the inverse Mills ratios to the correlation matrix in Tables 1 and A1. Notably, the correlations with our dependent measure are insignificant, indicating no severe selection biases (Certo et al., 2016).

TABLE 1 Bivariate correlations for calibrated scores in cross-border versus national alliances

	Calibrated variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Relative absorptive capacity A	1.00	−0.16	−0.02	−0.01	−0.07	0.00	−0.03	n/a	−0.11	**0.24**	−0.01	0.07	0.03	0.06	0.13	−0.08	−0.02	−0.05	−0.11	−0.12
2	Alliance-level digital technologies	0.00	1.00	0.02	−0.02	−0.04	0.10	0.10	n/a	0.13	0.10	**0.20**	−0.02	**0.17**	0.07	−0.09	0.05	0.14	0.04	0.14	−0.09
3	Relative firm size B/A	0.09	0.02	1.00	**0.57**	−0.01	0.12	0.13	n/a	**−0.18**	−0.13	**0.59**	0.10	**−0.16**	0.11	**−0.30**	**0.49**	**−0.41**	**−0.41**	**0.62**	**0.31**
4	Relative firm age B/A	0.06	0.03	**0.62**	1.00	0.07	**0.29**	0.13	n/a	**−0.17**	**−0.17**	**0.35**	−0.03	−0.07	0.15	**−0.26**	**0.34**	**−0.37**	**−0.60**	**0.33**	**0.61**
5	Technological distance	0.00	−0.07	−0.02	0.06	1.00	0.14	0.06	n/a	−0.14	**−0.21**	−0.14	−0.04	0.03	0.09	**−0.45**	−0.16	**−0.24**	−0.16	**−0.21**	0.00
6	Market distance	−0.02	−0.06	**−0.17**	**−0.16**	−0.11	1.00	0.01	n/a	−0.11	0.03	0.03	**−0.19**	0.03	0.07	−0.01	0.08	−0.16	−0.16	0.02	0.14
7	Geographic distance	−0.14	−0.03	0.00	0.08	−0.03	−0.03	1.00	n/a	0.01	−0.06	0.16	0.01	0.06	0.15	−0.13	0.09	−0.12	−0.10	0.03	0.04
8	Cultural distance (9D values)	−0.04	0.07	0.04	0.12	0.04	−0.02	**0.46**	1.00	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
9	Inverse Mills ratio	0.03	−0.02	**−0.21**	−0.09	−0.10	−0.01	**0.22**	**0.25**	1.00	0.06	−0.05	0.14	0.04	−0.11	0.16	−0.10	**0.47**	0.09	**0.23**	−0.16
10	% Digital intensity A pre	0.05	0.00	−0.11	−0.09	**−0.37**	**0.17**	0.06	−0.08	0.10	1.00	0.07	0.03	0.15	0.04	**0.48**	−0.14	**0.29**	**0.19**	0.16	−0.08
11	% Digital intensity B pre	0.15	0.09	**0.27**	**0.16**	**−0.32**	−0.01	0.11	0.07	**0.19**	0.03	1.00	0.04	−0.03	0.00	**−0.18**	**0.53**	−0.11	**−0.22**	**0.50**	0.16

(Continues)

TABLE 1 (Continued)

	Calibrated variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
12	Partner-specific alliance experience	0.08	−0.05	0.09	0.13	−0.01	−0.05	0.01	0.04	0.03	−0.09	**0.16**	1.00	−0.06	−0.10	0.00	−0.11	−0.03	0.01	−0.01	−0.04
13	General alliance experience A	0.11	0.11	−0.09	−0.03	**−0.24**	**0.28**	0.01	−0.11	0.03	**0.20**	**0.25**	0.00	1.00	0.03	0.02	−0.13	**0.22**	0.15	−0.01	0.04
14	% R&D intensity A	0.05	0.05	−0.01	0.08	−0.03	0.08	−0.04	−0.07	−0.03	0.07	−0.13	**−0.17**	0.07	1.00	−0.15	0.02	**−0.22**	**−0.30**	−0.02	−0.10
15	Exploration A	0.00	0.03	**−0.21**	**−0.23**	**−0.51**	0.12	0.06	−0.08	0.07	**0.54**	−0.09	−0.02	**0.17**	0.10	1.00	**−0.31**	**0.39**	**0.35**	−0.01	−0.02
16	Exploration B	0.01	0.06	**0.22**	**0.19**	**−0.38**	−0.04	0.03	−0.02	0.00	−0.02	**0.60**	0.02	0.13	−0.08	**−0.22**	1.00	−0.14	**−0.17**	**0.38**	**0.24**
17	Firm size A	0.01	**0.21**	**−0.38**	**−0.28**	**−0.31**	0.16	0.04	−0.04	**0.55**	**0.31**	**0.25**	−0.03	**0.22**	−0.01	**0.29**	**0.20**	1.00	**0.48**	**0.24**	−0.07
18	Firm age A	−0.05	0.02	**−0.29**	**−0.57**	−0.15	0.05	−0.13	−0.11	**0.23**	**0.18**	0.00	0.06	0.03	**−0.22**	**0.25**	−0.03	**0.49**	1.00	−0.04	0.14
19	Firm size B	0.00	0.14	**0.67**	**0.44**	−0.15	−0.08	−0.02	−0.07	0.12	0.13	**0.35**	0.02	0.11	0.07	−0.05	**0.32**	**0.22**	0.02	1.00	**0.29**
20	Firm age B	0.08	0.07	**0.54**	**0.64**	−0.05	−0.12	−0.01	0.04	0.03	0.06	**0.17**	0.14	−0.03	−0.09	−0.06	**0.24**	0.06	0.14	**0.56**	1.00

Note: $N = 148$ dyadic cross-border R&D alliances below diagonal and $N = 144$ dyadic national R&D alliances above diagonal; significant Pearson correlations are bold (p-value $\leq .05$).
Abbreviation: n/a, not available.

4.3 | Variables and calibration

The calibration process transforms raw data into fuzzy membership scores using set-theoretic thresholds as meaningful anchors (i.e., full-out at 0.05, crossover at 0.5, and full-in at 0.95). We used various data sources to minimize common method bias (Podsakoff et al., 2012). Our dependent measure is relative *absorptive learning capacity* (=ACap) by Fang and Zou (2010), which builds on three 5-point Likert-type items anchored at "1" (= strongly disagree) and "5" (= strongly agree). These three items reflect the extent to which the responding firm has developed a superior capability in (1) *understanding* (mean $M = 3.98$, std. deviation $SD = 0.88$, std. factor loading $\lambda = 0.71$), (2) *assimilating* ($M = 3.82$, $SD = 0.91$, $\lambda = 0.88$), and (3) *applying* the partner's knowledge and skills ($M = 3.79$, $SD = 1.03$, $\lambda = 0.72$). A main axis confirmatory factor analysis of this latent construct yields great reliability (composite reliability = 0.81), convergent validity by average variance extracted (AVE = 0.60), and discriminant validity by Fornell-Larcker ratio (FL = 0.02) (Fornell & Larcker, 1981). We calibrated these raw factor scores at typical levels of low and high membership (i.e., full-out = $-1 \triangleq$ cumulated empirical percentage 22%, cross-over = $0 \triangleq 46\%$, full-in = $+1 \triangleq 80\%$).

Our four dyadic alliance-level distance measures captured various aspects of non-directional (i.e., symmetrical) distances (Berry et al., 2010). First, we measured the *technological distance* between collaborating firms based on their IPC4-patent classes in the past 5 years. Of all commonly used symmetric measures (e.g., Euclidean distance, angle, correlation), we preferred the *min-complement technological distance* (calibration: full-out = $0 \triangleq 1\%$, cross-over = $0.8 \triangleq 9\%$, full-in = $1 \triangleq 22\%$), as this is the only one that satisfies the independence axiom (Bar & Leiponen, 2012). Second, we calculated *market distance* as the reverse market overlap (B.-J. Park et al., 2014; Yan et al., 2020) based on all 4-digit SIC codes both firms operate in to account for intra-alliance competition and industry-related structural commonalities (calibration: full-out = $0 \triangleq 4\%$, cross-over = $0.75 \triangleq 54\%$, full-in = $1 \triangleq 83\%$). Third, we measured *geographic distance* as the beeline between collaborating firms' headquarters in kilometers (calibration: full-out = 1 km $\triangleq$ 7%, cross-over = 500 km $\triangleq$ 51%, full-in = 10,000 km $\triangleq$ 97%). Fourth, regarding *cultural distance*, we applied the formula by Kogut and Singh (1988) to the country-level data of cultural *values* by House et al. (2006), consisting of nine dimensions (9D): assertiveness, institutional collectivism, in-group collectivism, future orientation, gender egalitarianism, humane orientation, performance orientation, power distance, and uncertainty avoidance (calibration: full-out = $0 \triangleq 50\%$, cross-over = $1.5 \triangleq 75\%$, full-in = $3 \triangleq 88\%$). Although geographic and cultural distances are highly correlated ($r = .65$, $p < .001$; international-only: $r = .42$, $p < .001$), there are empirical examples of asymmetrically calibrated combinations in our sample (e.g., "geo in–culture out": UK–Australia vs. "geo out–culture in": Belgium–France).

For measuring *digital technologies* at the alliance level, we asked respondents to indicate which of the following digital technologies were used in the focal R&D alliance (Pesch et al., 2021): 53% none versus 47% any (i.e., crisp-"or"-logic): 15% "industry 4.0," 14% "3D printing & additive manufacturing," 13% "big data analytics," 13% "cloud computing," 12% "robotics," 10% "cyber security," 8% "artificial intelligence," 6% "bots," 3% "telepresence & telemedicine," and 5% "other" (e.g., "3-D visualization & simulation software," "virtual & augmented reality," "wearable sensors").

As organizational learning processes in general (Ranger-Moore, 1997) and firms' absorptive capacity in particular (Lane et al., 2006) depend on firms' structural characteristics, we further calibrated firms' relative sizes (= number of partner firm's employees relative to responding firm's employees, calibration: full-out = -5 ln-transformed, i.e., responding firm is 100 times bigger ≙ 2%, cross-over = 0 ln-transformed, i.e., same firm sizes ≙ 38%, full-in = +5 ln-transformed, i.e., partner is 100 times bigger ≙ 88%) and relative ages (= years since both firms' incorporation, calibration: full-out = −2 ln-transformed, i.e., responding firm is 10 times older ≙ 3%, cross-over = 0 ln-transformed, i.e., same firm ages ≙ 45%, full-in = +2 ln-transformed, i.e., partner is 10 times older ≙ 96%).

Cognizant of the variable selection sensitivity of fsQCA results, we provide more context to interpret our findings in the post hoc analysis that examines additional variables suggested by theory (Greckhamer et al., 2013). First, we complemented alliance-level digital technologies with firm-level digital intensities in the 5 years pre-alliance formation based on patents filed in 4IR technology fields provided by Ménière et al. (2017). With just 3054 of all 67,020 unique IPC subgroups representing digital technology fields, the overall digitalization average is 4.6%. We applied a crisp logic for both firms if they filed any digital patents in the 5 years pre-alliance formation (Firm A: 19%, Firm B: 35%). Next, due to knowledge transfer and especially partner-specific absorptive capacity being time-dependent processes, we calibrated *partner-specific alliance experience* by the number of months since the alliance had been formed (calibration: full-out = 6 ≙ 1%, cross-over = 36 ≙ 51%, full-in = 120 ≙ 95%). In addition, we calibrated responding firms' *general alliance experience* (Hoang & Rothaermel, 2005) by the number of alliances formed in the 5 years pre-alliance formation (calibration: full-out = 0 ≙ 1%, cross-over = 10 ≙ 51%, full-in = 100 ≙ 91%). The responding firms' *R&D intensity* (Cohen & Levinthal, 1990) as percentages of firm sales spent on R&D often serves as a proxy of firm-level absorptive capacity (calibration: full-out = 0% ≙ 2%, cross-over = 10% ≙ 58%, full-in = 50% ≙ 95%). As an extension of alliance-level technological distance, we calculated firm-level *exploration* (Duysters et al., 2020) for both firms as the inverse of a normalized Herfindahl index, which captures the knowledge diversity of unique patent classes in the past 5 years pre-alliance formation (calibration: Firm A: full-out = 0.05 ≙ 0%, cross-over = 0.5 ≙ 56%, full-in = 0.95 ≙ 97%; Firm B: full-out = 0.05 ≙ 0%, cross-over = 0.5 ≙ 74%, full-in = 1 ≙ 97%). Last, we disaggregated relative firm size and age into separate firm characteristics (calibration: Firm A's size in number of employees: full-out = 10 ≙ 12%, cross-over = 50 ≙ 45%, full-in = 250 ≙ 74% & age in years: full-out = 5 ≙ 4%, cross-over = 25 ≙ 49%, full-in = 50 ≙ 76%; Firm B's size: full-out = 10 ≙ 10%, cross-over = 50 ≙ 29%, full-in = 250 ≙ 54% & age: full-out = 5 ≙ 5%, cross-over = 25 ≙ 43%, full-in = 50 ≙ 74%). Table 1 shows the bivariate correlations of calibrated scores in the cross-border and national subsamples.

5 | RESULTS

None of the variables are significantly correlated with responding firms' relative absorptive capacity (cf. first column of Table 1). Hence, we rely on alternative neo-configurational approaches. Notably, only Firm A's digital intensity is positively associated with ACap in *national* R&D alliances (cf. Table 1: $r_{nat} = 0.24$, $p = 0.004$ vs. $r_{int} = 0.05$, $p = 0.533$). We find that raw R&D expenses are a poor proxy for alliance-level ACap (cf. Table A1: $r = -0.05$, $p = 0.376$). Hence, we confirm that ACap is relative and should be assessed at the level of the learning dyad as "student-firm" and "teacher-firm" pairings (Lane & Lubatkin, 1998).

First, we set the maximum model complexity to seven (= k) conditions to reduce the extent of *limited diversity*. Generally, the theoretical number of configurations that double for every additional condition should not exceed the empirical sample sizes ($2^k = 2^7 = 128 < 148$ for cross-border & $2^6 = 64 < 144$ for national subsample without cultural distance). Following established guidelines (Ragin, 2008; Vis & Dul, 2016), we performed an *in-kind* necessity analysis of single conditions for high and low levels of ACap. Table 2 summarizes present and absent (=∼) single conditions by consistency and coverage levels. A consistency value greater than 0.9 constitutes a *general* necessary condition (Vis & Dul, 2016) of ACap or a lack thereof. Coverage values greater than 0.5 imply meaningful single causes. Remarkably, none of our core conditions (or remaining conditions in the correlation matrix) are consistent single necessary conditions of ACap or its absence in dyadic cross-border R&D alliances, further stressing the complexity of knowledge absorption across national borders. In the national sample, geographic proximity is the only consistent single necessary condition of ACap. This finding highlights the local embeddedness and contextuality of knowledge (Meyer et al., 2011; Nachum & Zaheer, 2005).

Next, we applied fsQCA to our seven core conditions leading to high or low ACap in the cross-border subsample (N = 148). The truth table for dyadic cross-border R&D alliances reveals 60 observed out of 128 theoretical configurations with N ≥ 1, expressing a moderate degree of limited diversity (with 47% of empirical representation). Table 3 summarizes four consistent (≥0.85) causal paths to high and seven consistent paths to low ACap in dyadic cross-border R&D alliances. Table A3 of the appendix shows the configurational solution for the national subsample ($N = 144$).

Notably, all paths to low ACap in cross-border R&D alliances are characterized by the presence of digital technologies, whereas high ACap reveals mixed configurations. *High 1a* and *low 2 e* only differ in their core conditions (i.e., parsimonious solution). These two culturally driven configurations are highly ambiguous: a focus on economies of scope (i.e., bigger partners) instead of competitive pressures (i.e., market similarity) renders high ACap and adds to the debate on the “double-edged sword of coopetition” (R. B. Bouncken & Kraus, 2013). Path *high 1b* and paths *low 2b* and *low 2c* differ in technological similarity. The multidimensional dissimilarity (i.e., technology, market, and geography) is probably too high of a burden for achieving high ACap. Both paths *high 1c* and *high 1d* lack digital technologies. These more traditional learning alliances (Hamel, 1991) build on complementarities and partner compatibility (Sarkar et al., 2001). In general, technological distance tends to be the biggest hurdle to achieving high ACap (*low 2a*, *2b*, *2c*, *2f*, *2 g*). The only two low technological distance paths are the ambiguous paths *low 2 e* and *low 2d*. The latter dysfunctional configuration suffers from too much similarity in all distance measures and a potential lack of trust (Sinkovics et al., 2021). These relatively young and small competitors are aware of the bigger partner's intention to absorb knowledge and are motivated to limit knowledge spillovers (M.-J. Chen et al., 2007).

In summary, we find only partial support for our proposed patterns. The only two paths to high absorptive capacity that strongly apply digital technologies (*high 1a* and *high 1b*) partly deviate from our proposed patterns: technological similarity is a pre-condition to using alliance-level digital technologies. Pattern 1 is mainly supported by path *high 1b*. Instead of the proposed low market distance in coopetition alliances, digital technologies can even bridge the high market distance between non-competitors. Pattern 1 is also partly supported by solution *high 1d* in a non-digital setting. Pattern 2 is partly supported. Both solutions *high 1a* and *high 1b* suggest asymmetric instead of symmetric combinations of geographic and cultural distances if the technological distance is low. A high cultural distance can spark high absorptive capacity through digital technologies, but only if no other distances are at play. However, this pattern remains highly ambiguous (cf. *high 1a* vs. *low 2 e*). Finally, Pattern 3 is mainly supported by solutions *high 1a* and *high 1b*, except for symmetric geographic and market distances as opposed to cultural distance in Pattern 2. Because of the relative size advantage, partner Firm B does not perceive the absorbing coopetitor A as a threat (cf. *high 1a*), even in geographic proximity (M.-J. Chen et al., 2007).

TABLE 2 QCA necessity analysis

	Absorptive capacity in INT		~Absorptive capacity in INT		Absorptive capacity in NAT		~Absorptive capacity in NAT	
	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage
Digital technologies	0.420	0.508	0.418	0.492	0.460	0.415	0.575	0.585
~Digital technologies	0.580	0.506	0.582	0.494	0.540	0.530	0.425	0.470
Relative firm sizes	0.729	0.613	0.691	0.565	0.734	0.561	0.733	0.632
~Relative firm sizes	0.482	0.616	0.526	0.653	0.518	0.633	0.490	0.675
Relative firm ages	0.656	0.629	0.639	0.596	0.658	0.594	0.654	0.667
~Relative firm ages	0.578	0.622	0.602	0.630	0.631	0.618	0.602	0.665
Technological distance	0.791	0.507	0.790	0.493	0.743	0.457	0.783	0.543
~Technological distance	0.209	0.506	0.210	0.494	0.257	0.512	0.217	0.488
Market distance	0.680	0.598	0.699	0.598	0.631	0.567	0.623	0.631
~Market distance	0.543	0.650	0.531	0.617	0.589	0.581	0.572	0.636
Geographic distance	0.758	0.563	0.815	0.588	0.308	0.696	0.305	0.777
~Geographic distance	0.445	0.713	0.394	0.614	0.901	0.535	0.881	0.589
Cultural distance	0.611	0.577	0.632	0.581	n/a	n/a	n/a	n/a
~Cultural distance	0.557	0.609	0.540	0.574	n/a	n/a	n/a	n/a

Note: ~ implies negated membership (= *fuzzynot*).
Abbreviations: INT, international; n/a, not available; NAT, national.

TABLE 3 Configurations for achieving (1) high versus (2) low ACap in cross-border R&D alliances

N≥1; C≥0.85	(1) High ACap				(2) Low ACap						
	1a	1b	1c	1d	2a	2b	2c	2d	2e	2f	2g
Alliance infrastructure											
1) Digital technologies	●	●	⨂	⨂	●	●	●	●	●	●	•
Firm characteristics											
2) Relatively bigger partner firm	●	●		•	⨂	●	●	⊗	•	⨂	⨂
3) Relatively older partner firm	⨂	⨂	⨂	●	⊗	⨂		⨂	⨂	●	●
Dyadic distances											
4) Technological distance	⨂	⨂	●	⨂	•	●	●	⨂	⨂	•	•
5) Market distance	⊗	•	⨂	⨂	•		●	⊗	⨂	⊗	⨂
6) Geographic distance	⊗	•	⨂	•	⨂	●	●	⨂	⊗	•	●
7) Cultural distance	•	⊗	⊗	⨂	⊗	⨂	⨂	⊗	•	⨂	⨂
Consistency	0.92 (0.87)	0.85 (0.87)	0.85 (0.83)	0.86 (0.85)	0.86 (0.82)	0.86 (0.86)	0.87 (0.87)	0.92 (0.63)	0.87 (0.71)	0.88 (0.82)	0.88 (0.80)
Raw coverage	0.02 (0.06)	0.03 (0.06)	0.11 (0.13)	0.03 (0.03)	0.09 (0.14)	0.10 (0.10)	0.12 (0.12)	0.02 (0.03)	0.02 (0.03)	0.07 (0.11)	0.07 (0.19)
Unique coverage	0.01 (0.06)	0.02 (0.06)	0.11 (0.13)	0.03 (0.03)	0.01 (0.04)	0.00 (0.00)	0.02 (0.02)	0.01 (0.00)	0.00 (0.01)	0.01 (0.01)	0.01 (0.10)
Overall solution consistency	**0.86 (0.85)**				**0.84 (0.76)**						
Overall solution coverage	**0.18 (0.22)**				**0.17 (0.31)**						

Note: Black circles indicate the presence, crossed white circles indicate the negation, and blank spaces signify the absence of a causal condition. Big circles indicate parsimonious solutions with fit evaluation in parentheses.

6 | DISCUSSION

Rooted in the emerging research on global connectivity (Cano-Kollmann et al., 2016; Castellani et al., 2022; Goerzen, 2018; Lorenzen & Mudambi, 2013; Sinkovics et al., 2019; Turkina et al., 2016; Turkina & Van Assche, 2018), the motivation for our study is that firms increasingly aim to absorb technologies and knowledge from a variety of international locations using cross-border R&D alliances (Awate et al., 2015; Berry, 2014; Cantwell, 1989; Mudambi et al., 2018). In pursuit of absorptive capacity in such alliances, firms face ambiguous merits and challenges related to implementing digital technology (Autio et al., 2021). We support the idea that digital technology implementation can facilitate a "flatter" world and simultaneously create "spikes" in the global economy, dependent on a multiplicity of causal recipes (Mithas & Whitaker, 2007; Y. Park et al., 2020). However, the corresponding knowledge has some stickiness, which reduces its transferability via digital technology (Szulanski, 1996). Potential challenges of digital technology implementation for absorptive capacity purposes are especially pronounced in cross-border R&D alliances because valuable and tacit knowledge transfer is more crucial for "resource seekers" (Zaheer & Manrakhan, 2001, p. 671) than substituting physical transfers with digital ones (Kang & Zaheer, 2018; Nachum & Zaheer, 2005; Zaheer et al., 2012).

6.1 | Contribution—Technological similarity and digitalization biases

Our finding that digital technology implementation is rarely helpful in achieving absorptive capacity in R&D alliances might not appear surprising, considering digital technology's known limitations in transferring tacit knowledge. Specifically, we contribute to previous ambivalent findings about the merits and challenges of digital technology use across the various forms of distance (Cano-Kollmann et al., 2016; Kang & Zaheer, 2018; Liao et al., 2007; Nachum &

Zaheer, 2005; Nambisan et al., 2017; Setia et al., 2013; Törnroos et al., 2017; Turkina et al., 2016; Turkina & Van Assche, 2018; Zaheer et al., 2012). Our findings are striking in that only two of our identified configurations implement digital technology successfully, and because we identified the supportive pattern of causal recipes for achieving absorptive capacity.

The challenges of relying on digital technology within cross-border R&D alliances are multifaceted, as shown by our finding that alliance-level digital technology implementation is present in all low absorptive capacity configurations and only two out of four high configurations. Our configurational study design reveals important patterns in which firms do not choose an appropriate setup for absorptive capacity creation, which is an integral part of R&D processes. The digital technology implementation might be used for substituting physical transfers with digital ones in operational processes but not for tacit knowledge transfer in R&D alliances (Kang & Zaheer, 2018; Nachum & Zaheer, 2005; Zaheer et al., 2012).

Although firms are increasingly eager to grasp the potential of digital technology, R&D alliances appear to involve substantial limitations and risks of overrating such potential. This might be because firms rely on surface-level advantages related to the easy transfer of digitalized processes and objects and accessible virtual communication. Firms might overestimate the easiness and usability of digital technology, as quoted in the "virtuality trap" (Yamin & Sinkovics, 2006). As documented in all low configurations, (over-)reliance on digital technologies can negatively affect firms' absorptive capacity. This is in line with virtual meetings fostering more handshake exchanges than in-depth conversations (Leamer & Storper, 2001).

Absorptive capacity development might require more detail concerning the use of digital technology, the data origin, the data context, and how different persons interpret the data in diverse contexts. Absorptive learning processes across firms require individuals to become more familiar and empowered to better interpret the contextualized knowledge in digital exchanges—and this seems difficult via digital technology. Most low configurations applied digital technologies in technologically distant yet culturally close cross-border R&D alliances, potentially failing to deconstruct and reconnect underlying knowledge bases. In this regard, we relate to but also make previous research on the limitations of digital technology for exchanging sticky or contextually embedded knowledge more specific (Nachum & Zaheer, 2005). We especially emphasize the shortcomings of digital technologies with respect to mainly transferring codified knowledge or permitting only temporary or surface-level information exchanges. Our findings further align with the eclectic model of internal stickiness by Szulanski (1996), who suggests considering the characteristics of (1) the knowledge transferred, (2) the source, (3) the recipient, and (4) the context of knowledge transfer all at once.

We assume that when digital technology is substantially implemented in cross-border alliances, absorption demands a sufficient level of understanding and detail among the allying firms, especially on technological aspects. Higher levels of distance might induce misunderstanding, misinterpretation, and related dysfunctional processes in the knowledge transfer, limiting the realized absorptive capacity through fragmentation and black-boxing (Anthony, 2021; Jansen et al., 2005). In this, our findings support previous research that emphasized specificities of contexts and the personal exchanges that might complicate successfully learning and exchanging knowledge in digitalized contexts (Cano-Kollmann et al., 2016; Kang & Zaheer, 2018; Liao et al., 2007; Nachum & Zaheer, 2005; Nambisan et al., 2017; Setia et al., 2013; Törnroos et al., 2017; Zaheer et al., 2012).

Although understanding, assimilating, and independently applying a partner's knowledge and skills should be the preferred outcomes in a scenario characterized by power plays, asymmetric dependency, constant bargaining, and competitive pressures (R. B. Bouncken et al., 2020; R. B. Bouncken & Fredrich, 2011; C.-J. Chen, 2004; Fredrich et al., 2019; Matthyssens et al., 2005), there might be an alternative interpretation of low configurations. Digital technologies can be powerful instruments specifically designed to offset the negative consequences of low levels of absorptive capacity. For example, individuals who trust the outcomes of machine learning algorithms without understanding them (i.e., black-boxing) may not necessarily make worse decisions. Still, there might be long-term consequences for their career trajectories (Anthony, 2021).

In sum, the above discussion emphasizes the risk of taking for granted the surface-level benefits of digital technology for absorptive capacity while ignoring the challenges and the necessary level of detail in R&D processes. This cognitive bias prevails because firms seem to insufficiently consider how much more depth they need in their (personal) conversations, technology fit, discussion, and (de-)contextualization of location and cultural specificity. We speculate that the mere presence of alliance-level digital technology might create an illusion and overreaching image of absorption merits.

These challenges are generally lower when firms have a high technological similarity. Our nuanced finding on the two successful paths to high absorptive capacity supports and refines this cognitive bias that stems from too many surface-level considerations and overestimating merits while ignoring the context and necessary detail. This is most obvious in that we find high absorptive capacity contingent on high technological overlap among the firms and on being the older and smaller firm. The higher level of technological overlap signals that firms better and more "naturally" understand each other's R&D content. In this, we reveal a consistent boundary condition related to technological similarity and learning from technological similarity (Yan et al., 2020). The mutual understanding of technologies supports knowledge absorption processes and renders the limitations of digital technology implementation less critical while lifting its advantages.

In addition, we find favorable configurations of smaller and older firms. These firms enter a typical teacher–student situation (Lane et al., 2001; Kim & Inkpen, 2005), meaning that there is great attention to learning and depth. The two configurations of asymmetric learning dyads (Lane & Lubatkin, 1998) only differ in their peripheral conditions, which yet emphasize the cross-cultural background of our study. Given the easy knowledge absorption using digital technologies under low technological distance, the level of cultural distance determines whether geographic and market distances can be bridged (Steensma et al., 2000; Turkina & Van Assche, 2018). The high cultural distance can spark high absorptive capacity through digital technologies, but only if no other distances are at play. The configuration also ties in with research about power imbalances and coopetitive tensions arising from technological, market, and geographic proximity (Fredrich et al., 2019; Tidström, 2014). We assume cultural diversity and the smaller firm being perceived as no threat to the bigger partner can offset the associated risks (C.-J. Chen et al., 2007). The mirroring configuration includes high market and geographic distances accompanied by low cultural distance.

Our findings are not solely pessimistic about digital technology implementation in R&D alliances. Potential merits of knowledge transfer via digital technology (Cherbib et al., 2021; Lorenzen et al., 2020) arise when there is high technological overlap and the potential to learn—either from a low or high cultural distance. Past studies have investigated digital solutions, digitalized transfers (Lorenzen et al., 2020; Tallman et al., 2018), and virtual person-to-person communication (Forman & van Zeebroeck, 2019). Our study focused on R&D alliances; hence, the question of how digital technology might reduce transportation for the manufacturing of physical goods (Castellani et al., 2013) was less of a concern in our setting. Although digital technologies can be leveraged to foster the understanding, assimilation, and application of knowledge in strategic alliances (Ardito et al., 2021; R. Bouncken & Barwinski, 2021), they do not necessarily bridge the technological distance. Still, firms—supposedly resource seekers (Zaheer & Manrakhan, 2001, p. 671)—might also need to transfer physical goods and personnel for their R&D. For R&D, knowledge transfer—and hence absorptive capacity—becomes most meaningful for managing knowledge embeddedness. Yet, the transfer of contextualized or tacit knowledge is not always met by the necessarily shared digital identity (R. Bouncken & Barwinski, 2021) and might underlie some trajectories (R. Bouncken & Tiberius, 2021). Spatial characteristics of the two locations in which the dyadic partners are embedded and technological specificity can limit the knowledge transfer via digital technology (Cano-Kollmann et al., 2016; Hanelt et al., 2021; Liao et al., 2007; Nambisan et al., 2017; Setia et al., 2013; Törnroos et al., 2017). As previous research is ambiguous and multifaceted regarding how digital technology implementation influences cross-border R&D alliances, our configurational findings contribute to the emerging research on digital media and cross-cultural knowledge contextualization.

Again, we highlight that digital technology bears cognitive digitalization biases and pitfalls in cross-border R&D alliances. Firms need to work on R&D processes, which are often uncertain and dynamic, and draw on digital technology that is not ideally suited for the underlying creativity processes, causing intra-task and interpersonal conflicts due to misunderstanding, miscommunication, and a lack of copresence and adaptability. Digital technology implementation demands attention and effort from the individuals in the R&D alliance, and might distract them from their knowledge work (Orhan et al., 2021). More precisely, we propose cognitive biases of taking digital technology merits for granted, underestimating their challenges and the necessary level of detail, and not paying sufficient attention to the offline context, which tends to be complex and dynamic in cross-border R&D alliances. Previous research has noted that over-reliance on new information and communication technologies (ICT) without sufficient contextual knowledge can cause early adopters to fall into a virtuality trap (Sinkovics et al., 2013; Yamin & Sinkovics, 2006). The virtuality trap was initially articulated in the context of early Internet business but had again gained relevance in today's more advanced stages of digital transformation. Similar to the dot.com-bubble of the 2000s, not fully understanding the conditions under which digital technologies can be effectively leveraged can lead to a virtuality trap (Yamin & Sinkovics, 2006). Although the ongoing digital transformation benefits R&D alliances, our configurational findings suggest that organizational reality has not yet caught up to the promise of these technologies.

Related to the potential cognitive biases and paying too much attention to the surface-level of generic digital technology benefits, firms should pay close attention to investments and costs for understanding, adapting, improving, or developing digital technology. Firms might have little additional time, resources, or slack to absorb knowledge from their ongoing R&D alliances. Consequently, individuals in the cross-border R&D alliance might experience individual-level technostress using digital technologies (Maier et al., 2022). Perceived technostress might spiral to the group or organizational level, and organizational technostress might soak up knowledge processes and limit the realized absorptive capacity.

In brief, we conclude that cross-border R&D alliances that implement digital technologies can achieve high levels of absorptive capacity by (1) selecting bigger and younger partners, (2) assuring technological similarity, and (3) coping with potential cognitive biases associated with overestimating benefits and underestimating challenges of digital technology implementation—for example, the contextual embeddedness of knowledge, black-boxing, and technostress.

6.2 | Limitations and future research directions

A limitation of our study is measuring cultural distance via country-level values related to the firms' locations, thereby assuming symmetric distances (i.e., A − B = B − A) and neglecting within-country variance (Peterson & Søndergaard, 2014; Tung & Verbeke, 2010). We expect more nuanced findings from analyzing cultural profiles, artifacts, and meaningful confounders directly measured at the alliance level (e.g., firms' corporate cultures, working hours, remote work). Similarly, we advocate a more balanced treatment of culture in IB studies (Stahl & Tung, 2015) and expect meaningful insights by considering the perceived cultural distance and attitude toward cultural intelligence (Pesch & Bouncken, 2018). For a better understanding of cultural differences, future research might expand on the concept of psychic distance and how it affects the implementation of digital technology. Notably, geographic distance accounts for the largest share of the explained variance of perceived psychic distance in past studies (Håkanson & Ambos, 2010).

Our post hoc analysis revealed that absorptive capacity and digital technologies could reduce unintended alliance termination in *national* R&D alliances, minimizing sunk costs from R&D alliance failure (S. H. Park & Ungson, 2001). Future studies might investigate the conflict resolution capabilities of digital technologies and suggest a more harmonized digital value creation and capture at the alliance level (Cappa et al., 2021).

Reflecting on our insights into decision-making biases in alliances (Chao, 2011), we recommend an experimental design and measuring the perceived technostress. Technostress mainly occurs in the early stages of technology implementation (Maier et al., 2022), calling for longitudinal analysis of its consequences within and across different levels. Furthermore, future studies should consider digital technology experience at the firm level as this drives firms' exploration tendencies in our data. Last, we acknowledge that our one-sided perception of responding firms' absorptive capacity can only incompletely capture potentially asymmetric learning dynamics of "digital learning races" in R&D alliances between teachers who become students and vice versa.

ACKNOWLEDGMENT

Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST

The authors declare no potential conflict of interests.

ORCID

Ricarda B. Bouncken https://orcid.org/0000-0003-0510-7491
Viktor Fredrich https://orcid.org/0000-0001-9646-4173
Noemi Sinkovics https://orcid.org/0000-0002-5143-6870
Rudolf R. Sinkovics https://orcid.org/0000-0002-4471-5054

REFERENCES

Ahi, A. A., Sinkovics, N., Shildibekov, Y., Sinkovics, R. R., & Mehandjiev, N. (2021). Advanced technologies and international business: A multidisciplinary analysis of the literature. *International Business Review*, *31*(4), 101967.

Ambos, B., & Håkanson, L. (2014). The concept of distance in international management research. *Journal of International Management*, *20*(1), 1–7.

Anthony, C. (2021). When knowledge work and analytical technologies collide: The practices and consequences of black boxing algorithmic technologies. *Administrative Science Quarterly*, *66*(4), 1173–1212.

Ardanza, A., Moreno, A., Segura, Á., de la Cruz, M., & Aguinaga, D. (2019). Sustainable and flexible industrial human machine interfaces to support adaptable applications in the Industry 4.0 paradigm. *International Journal of Production Research*, *57*(12), 4045–4059.

Ardito, L., Cerchione, R., Mazzola, E., & Raguseo, E. (2021). Industry 4.0 transition: a systematic literature review combining the absorptive capacity theory and the data–information–knowledge hierarchy. *Journal of Knowledge Management*, *26*(9), 2222–2254.

Autio, E., Mudambi, R., & Yoo, Y. (2021). Digitalization and globalization in a turbulent world: Centrifugal and centripetal forces. *Global Strategy Journal*, *11*(1), 3–16.

Awate, S., Larsen, M. M., & Mudambi, R. (2015). Accessing vs sourcing knowledge: A comparative study of R&D internationalization between emerging and advanced economy firms. *Journal of International Business Studies*, *46*(1), 63–86.

Bar, T., & Leiponen, A. (2012). A measure of technological distance. *Economics Letters*, *116*(3), 457–459.

Barnett, M., Henriques, I., & Husted, B. (2021). Family matters? The effects of size and proximity in the digital age. *Academy of Management Perspectives*, *35*(3), 557–561.

Baur, C., & Wee, D. (2015). *Manufacturing's next act*. https://timereaction.com/papers/manufacturing_next_act.pdf

Becker, J., Berger, M., Gimpel, H., Lanzl, J., & Regal, C. (2020). *Considering characteristic profiles of technologies at the digital workplace: The influence on technostress*. Paper presented at the Forty-First International Conference on Information Systems, India.

Berry, H. (2014). Global integration and innovation: Multicountry knowledge generation within MNCs. *Strategic Management Journal*, *35*(6), 869–890.

Berry, H., Guillén, M. F., & Zhou, N. (2010). An institutional approach to cross-national distance. *Journal of International Business Studies*, *41*(9), 1460–1480.

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, *37*(2), 471–482.

Biemann, T., & Kearney, E. (2010). Size does matter: How varying group sizes in a sample affect the most common measures of group diversity. *Organizational Research Methods*, *13*(3), 582–599.

Bouncken, R., & Barwinski, R. (2021). Shared digital identity and rich knowledge ties in global 3D printing—A drizzle in the clouds? *Global Strategy Journal*, *11*(1), 81–108.

Bouncken, R., & Kraus, S. (2014). Does national culture matter? Performance effects in global innovation teams. *European Journal of Management*, *14*(3), 87–96.

Bouncken, R., & Tiberius, V. (2021). Legitimacy processes and trajectories of co-prosumption services: Insights from coworking spaces. *Journal of Service Research* in press.

Bouncken, R. B., & Fredrich, V. (2011). *Coopetition: Its successful management in the nexus of dependency and trust*. Paper presented at the 2011 Proceedings of PICMET'11: Technology Management in the Energy Smart World (PICMET).

Bouncken, R. B., Fredrich, V., & Kraus, S. (2020). Configurations of firm-level value capture in coopetition. *Long Range Planning*, *53*(1), 101869.

Bouncken, R. B., & Kraus, S. (2013). Innovation in knowledge-intensive industries: The double-edged sword of coopetition. *Journal of Business Research*, *66*(10), 2060–2070.

Bouncken, R. B., & Winkler, V. A. (2010). National and cultural diversity in transnational innovation teams. *Technology Analysis & Strategic Management*, *22*(2), 133–151.

Cano-Kollmann, M., Cantwell, J., Hannigan, T. J., Mudambi, R., & Song, J. (2016). Knowledge connectivity: An agenda for innovation research in international business. *Journal of International Business Studies*, *47*(3), 255–262.

Cantwell, J. (1989). *Technological innovation and multinational corporations*. Cambridge, MA: Basil Blackwell.

Cappa, F., Oriani, R., Peruffo, E., & McCarthy, I. (2021). Big data for creating and capturing value in the digitalized environment: Unpacking the effects of volume, variety, and veracity on firm performance. *Journal of Product Innovation Management*, *38*(1), 49–67.

Castellani, D., Jimenez, A., & Zanfei, A. (2013). How remote are R&D labs? Distance factors and international innovative activities. *Journal of International Business Studies*, *44*(7), 649–675.

Castellani, D., Lavoratori, K., Perri, A., & Scalera, V. G. (2022). International connectivity and the location of multinational enterprises' knowledge-intensive activities: Evidence from US metropolitan areas. *Global Strategy Journal*, *12*(1), 82–107.

Catalini, C., Fons-Rosen, C., & Gaule, P. (2020). How do travel costs shape collaboration? *Management Science*, *66*(8), 3340–3360.

Cennamo, C. (2021). Competing in digital markets: A platform-based perspective. *Academy of Management Perspectives*, *35*(2), 265–291.

Certo, S. T., Busenbark, J. R., Woo, H. s., & Semadeni, M. (2016). Sample selection bias and Heckman models in strategic management research. *Strategic Management Journal*, *37*(13), 2639–2657.

Chao, Y. C. (2011). Decision-making biases in the alliance life cycle: Implications for alliance failure. *Management Decision*, *49*(3), 350–364.

Chen, C.-J. (2004). The effects of knowledge attribute, alliance characteristics, and absorptive capacity on knowledge transfer performance. *R&D Management*, *34*(3), 311–321.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, *36*(4), 1165–1188.

Chen, M.-J., Su, K.-H., & Tsai, W. (2007). Competitive tension: The awareness–motivation–capability perspective. *Academy of Management Journal*, *50*(1), 101–118.

Cherbib, J., Chebbi, H., Yahiaoui, D., Thrassou, A., & Sakka, G. (2021). Digital technologies and learning within asymmetric alliances: The role of collaborative context. *Journal of Business Research*, *125*, 214–226.

Choi, J., & Contractor, F. J. (2016). Choosing an appropriate alliance governance mode: The role of institutional, cultural and geographical distance in international research & development (R&D) collaborations. *Journal of International Business Studies*, *47*(2), 210–232.

Chu, J., & Manchanda, P. (2016). Quantifying cross and direct network effects in online consumer-to-consumer platforms. *Marketing Science*, *35*(6), 870–893.

Chung, S. A., Singh, H., & Lee, K. (2000). Complementarity, status similarity and social capital as drivers of alliance formation. *Strategic Management Journal*, *21*(1), 1–22.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152.

Cui, A. S., & O'Connor, G. (2012). Alliance portfolio resource diversity and firm innovation. *Journal of Marketing*, *76*(4), 24–43.

de la Torre, J., & Moxon, R. W. (2001). Introduction to the symposium e-commerce and global business: The impact of the information and communication technology revolution on the conduct of international business. *Journal of International Business Studies*, *32*(4), 617–639.

De Luca, L. M., & Atuahene-Gima, K. (2007). Market knowledge dimensions and cross-functional collaboration: Examining the different routes to product innovation performance. *Journal of Marketing*, *71*(1), 95–112.

Delgado, M., Porter, M. E., & Stern, S. (2010). Clusters and entrepreneurship. *Journal of Economic Geography*, *10*(4), 495–518.

Doloreux, D., & Turkina, E. (2021). New path creation in the artificial intelligence industry: Regional preconditions, new actors and their collective actions, and policies. *Regional Studies*, *55*(10–11), 1751–1763.

Dow, D. (2017). Are we at a turning point for distance research in international business studies? In A. Verbeke, J. Puck, & R. V. Tulder (Eds.), *Distance in international business: Concept, cost and value* (Vol. 12, pp. 47–68). Bingley, UK: Emerald Publishing.

Dul, J. (2016). Necessary condition analysis (NCA): Logic and methodology of "necessary but not sufficient" causality. *Organizational Research Methods*, *19*(1), 10–52.

Dul, J. (2019). *Necessary condition analysis*. R Package Version 3.0.2. http://cran.r-project.org/web/packages/NCA/

Duysters, G., Lavie, D., Sabidussi, A., & Stettner, U. (2020). What drives exploration? Convergence and divergence of exploration tendencies among alliance partners and competitors. *Academy of Management Journal*, *63*(5), 1425–1454.

Eberhard, D. M., Simons, G. F., & Fennig, C. D. (2020). In D. M. Eberhard, G. F. Simons, & C. D. Fennig (Eds.), *Ethnologue: Languages of the world* (23rd ed.). Dallas, TX: SIL International. http://www.ethnologue.com

Eriksson, R. H. (2011). Localized spillovers and knowledge flows: How does proximity influence the performance of plants? *Economic Geography*, *87*(2), 127–152.

Fainshmidt, S., Witt, M. A., Aguilera, R. V., & Verbeke, A. (2020). The contributions of qualitative comparative analysis (QCA) to international business research. *Journal of International Business Studies*, *51*(4), 455–466.

Fang, E., & Zou, S. (2010). The effects of absorptive and joint learning on the instability of international joint ventures in emerging economies. *Journal of International Business Studies*, *41*(5), 906–924.

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, *54*(2), 393–420.

Forman, C., & van Zeebroeck, N. (2019). Digital technology adoption and knowledge flows within firms: Can the Internet overcome geographic and technological distance? *Research Policy*, *48*(8), 103697.

Fornell, C., & Larcker, D. F. (1981). Evaluation structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(February), 39–50.

Fredrich, V., Bouncken, R. B., & Kraus, S. (2019). The race is on: Configurations of absorptive capacity, interdependence and slack resources for interorganizational learning in coopetition alliances. *Journal of Business Research*, *101*, 862–868.

Ganzach, Y. (1998). Nonlinearity, multicollinearity and the probability of type II error in detecting interaction. *Journal of Management*, *24*(5), 615–622.

Gnyawali, D. R., & Park, B.-J. R. (2011). Co-opetition between giants: Collaboration with competitors for technological innovation. *Research Policy*, *40*(5), 650–663.

Goerzen, A. (2018). Small firm boundary-spanning via bridging ties: Achieving international connectivity via cross-border inter-cluster alliances. *Journal of International Management*, *24*(2), 153–164.

Gopalakrishnan, S., & Bierly, P. E. (2006). The impact of firm size and age on knowledge strategies during product development: A study of the drug delivery industry. *IEEE Transactions on Engineering Management*, *53*(1), 3–16.

Greckhamer, T., Misangyi, V. F., & Fiss, P. C. (2013). The two QCAs: From a small-N to a large-N set theoretic approach. In P. C. Fiss, B. Cambré, & A. Marx (Eds.), *Configurational theory and methods in organizational research* (Vol. 38, pp. 49–75). Bradfort: Emerald Group Publishing.

Gregory, R. W., Henfridsson, O., Kaganer, E., & Kyriakou, H. (2022). Data network effects: Key conditions, shared data, and the data value duality. *Academy of Management Review*, *47*(1), 189–192.

Håkanson, L., & Ambos, B. (2010). The antecedents of psychic distance. *Journal of International Management*, *16*(3), 195–210.

Hamel, G. (1991). Competition for competence and inter-partner learning within international strategic alliances. *Strategic Management Journal*, *12*(4), 83–103.

Hanelt, A., Firk, S., Hildebrandt, B., & Kolbe, L. M. (2021). Digital M&A, digital innovation, and firm performance: An empirical investigation. *European Journal of Information Systems*, *30*(1), 3–26.

Harrison, J. S., Hitt, M. A., Hoskisson, R. E., & Ireland, R. D. (2001). Resource complementarity in business combinations: Extending the logic to organizational alliances. *Journal of Management*, *27*(6), 679–690.

He, Q., Meadows, M., Angwin, D., Gomes, E., & Child, J. (2020). Strategic alliance research in the era of digital transformation: Perspectives on future research. *British Journal of Management*, *31*(3), 589–617.

Hoang, H., & Rothaermel, F. T. (2005). The effect of general and partner-specific alliance experience on joint R&D project performance. *Academy of Management Journal*, *48*(2), 332–345.

Horváth, D., & Szabó, R. Z. (2019). Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities? *Technological Forecasting and Social Change*, *146*(June), 119–132.

House, R. J., Hanges, P. J., Javidan, M., Dorfman, P. W., & Gupta, V. (Eds.). (2006). *Culture, leadership and organizations. The globe study of 62 societies*. Thousand Oaks: Sage Publications.

Jansen, J. J. P., Van den Bosch, F. A. J., & Volberda, H. W. (2005). Managing potential and realized absorptive capacity: How do organizational antecedent's matter? *Academy of Management Journal*, *48*(6), 999–1015.

Kang, R., & Zaheer, A. (2018). Determinants of alliance partner choice: Network distance, managerial incentives, and board monitoring. *Strategic Management Journal*, *39*(10), 2745–2769.

Kim, C.-S., & Inkpen, A. C. (2005). Cross-border R&D alliances, absorptive capacity and technology learning. *Journal of International Management*, *11*(3), 313–329.

Kleis, L., Chwelos, P., Ramirez, R. V., & Cockburn, I. (2012). Information technology and intangible output: The impact of IT investment on innovation productivity. *Information Systems Research*, *23*(1), 42–59.

Knein, E., Greven, A., Bendig, D., & Brettel, M. (2020). Culture and cross-functional coopetition: The interplay of organizational and national culture. *Journal of International Management*, *26*(2), 100731.

Kogut, B., & Singh, H. (1988). The effect of national culture on the choice of entry mode. *Journal of International Business Studies*, *19*(3), 411–432.

Krogslund, C., Choi, D. D., & Poertner, M. (2015). Fuzzy sets on shaky ground: Parameter sensitivity and confirmation bias in fsQCA. *Political Analysis*, *23*(1), 21–41.

Lane, P. J., Koka, B. R., & Pathak, S. (2006). The reification of absorptive capacity: A critical review and rejuvenation of the construct. *Academy of Management Review*, *31*(4), 833–863.

Lane, P. J., & Lubatkin, M. (1998). Relative absorptive capacity and interorganizational learning. *Strategic Management Journal*, *19*(5), 461–477.

Lane, P. J., Salk, J. E., & Lyles, M. A. (2001). Absorptive capacity, learning, and performance in international joint ventures. *Strategic Management Journal*, *22*(12), 1139–1161.

Lanzolla, G., Pesce, D., & Tucci, C. L. (2021). The digital transformation of search and recombination in the innovation function: Tensions and an integrative framework. *Journal of Product Innovation Management*, *38*(1), 90–113.

Leamer, E. E., & Storper, M. (2001). The economic geography of the internet age. *Journal of International Business Studies*, *32*(4), 641–666.

Lee, S. M., & Trimi, S. (2021). Convergence innovation in the digital age and in the COVID-19 pandemic crisis. *Journal of Business Research*, *123*, 14–22.

Liao, S.-H., Fei, W.-C., & Chen, C.-C. (2007). Knowledge sharing, absorptive capacity, and innovation capability: An empirical study of Taiwan's knowledge-intensive industries. *Journal of Information Science*, *33*(3), 340–359.

Lin, C. H., Wu, Y. J., Chang, C. C., Wang, W. H., & Lee, C. Y. (2012). The alliance innovation performance of R&D alliances-the absorptive capacity perspective. *Technovation*, *32*(5), 282–292.

Liu, Y., & Ravichandran, T. (2015). Alliance experience, IT-enabled knowledge integration, and ex ante value gains. *Organization Science*, *26*(2), 511–530.

Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. *The Journal of Strategic Information Systems*, *24*(3), 149–157.

Lorenzen, M., & Mudambi, R. (2013). Clusters, connectivity and catch-up: Bollywood and Bangalore in the global economy. *Journal of Economic Geography*, *13*(3), 501–534.

Lorenzen, M., Mudambi, R., & Schotter, A. (2020). International connectedness and local disconnectedness: MNE strategy, city-regions and disruption. *Journal of International Business Studies*, *51*(8), 1199–1222.

Maier, C., Laumer, S., Thatcher, J. B., Wirth, J., & Weitzel, T. (2022). Trial-period technostress: A conceptual definition and mixed-methods investigation. *Information Systems Research*, *33*(2), 489–514.

Martin, X., & Salomon, R. (2003). Tacitness, learning, and international expansion: A study of foreign direct investment in a knowledge-intensive industry. *Organization Science*, *14*(3), 297–311.

Maseland, R., Dow, D., & Steel, P. (2018). The Kogut and Singh national cultural distance index: Time to start using it as a springboard rather than a crutch. *Journal of International Business Studies*, *49*(9), 1154–1166.

Matthyssens, P., Pauwels, P., & Vandenbempt, K. (2005). Strategic flexibility, rigidity and barriers to the development of absorptive capacity in business markets: Themes and research perspectives. *Industrial Marketing Management*, *34*(6), 547–554.

Ménière, Y., Rudyk, I., & Valdes, J. (2017). *Patents and the fourth industrial revolution*. Munich: European Patent Office.

Meyer, K. E., Mudambi, R., & Narula, R. (2011). Multinational enterprises and local contexts: The opportunities and challenges of multiple embeddedness. *Journal of Management Studies*, *48*(2), 235–252.

Misangyi, V. F., Greckhamer, T., Furnari, S., Fiss, P. C., Crilly, D., & Aguilera, R. (2017). Embracing causal complexity: The emergence of a neo-configurational perspective. *Journal of Management*, *43*(1), 255–282.

Mithas, S., Tafti, A. R., Bardhan, I., & Goh, J. M. (2012). Information technology and firm profitability: Mechanisms and empirical evidence. *MIS Quarterly*, *36*(1), 205–224.

Mithas, S., & Whitaker, J. (2007). Is the world flat or spiky? Information intensity, skills, and global service disaggregation. *Information Systems Research*, *18*(3), 237–259.

Mudambi, R., Li, L., Ma, X., Makino, S., Qian, G., & Boschma, R. (2018). Zoom in, zoom out: Geographic scale and multinational activity. *Journal of International Business Studies*, *49*(8), 929–941.

Nachum, L., & Zaheer, S. (2005). The persistence of distance? The impact of technology on MNE motivations for foreign investment. *Strategic Management Journal*, *26*(8), 747–767.

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.

Narula, R., & Santangelo, G. D. (2009). Location, collocation and R&D alliances in the European ICT industry. *Research Policy*, *38*(2), 393–403.

Nwankpa, J. K., & Datta, P. (2017). Balancing exploration and exploitation of IT resources: The influence of digital business Intensity on perceived organizational performance. *European Journal of Information Systems*, *26*(5), 469–488.

Orhan, M. A., Castellano, S., Khelladi, I., Marinelli, L., & Monge, F. (2021). Technology distraction at work. Impacts on self-regulation and work engagement. *Journal of Business Research*, *126*, 341–349.

Oxley, J. E., & Sampson, R. C. (2004). The scope and governance of international R&D alliances. *Strategic Management Journal*, *25*(8–9), 723–749.

Park, B.-J., Srivastava, M. K., & Gnyawali, D. R. (2014). Walking the tight rope of coopetition: Impact of competition and cooperation intensities and balance on firm innovation performance. *Industrial Marketing Management*, *43*(2), 210–221.

Park, S. H., & Ungson, G. R. (2001). Interfirm rivalry and managerial complexity: A conceptual framework of alliance failure. *Organization Science*, *12*(1), 37–53.

Park, Y., Fiss, P. C., & El Sawy, O. A. (2020). Theorizing the multiplicity of digital phenomena: The ecology of configurations, causal recipes, and guidelines for applying QCA. *MIS Quarterly*, *44*(4), 1493–1520.

Pesch, R., & Bouncken, R. B. (2017). The double-edged sword of cultural distance in international alliances—How perceived cultural distance influences trust and task discourse to drive new product development performance. *Cross Cultural & Strategic Management*, *24*(1), 33–54.

Pesch, R., & Bouncken, R. B. (2018). How to achieve benefits from diversity in international alliances: Mechanisms and cultural intelligence. *Global Strategy Journal*, *8*(2), 275–300.

Pesch, R., Endres, H., & Bouncken, R. B. (2021). Digital product innovation management: Balancing stability and fluidity through formalization. *Journal of Product Innovation Management*, *38*, 726–744.

Peterson, M. F., & Søndergaard, M. (2014). Countries, within-country regions, and multiple-country regions in international management: A functional, institutional, and critical event (FICE) perspective. *Management International Review*, *54*(6), 781–800.

Peterson, M. F., Søndergaard, M., & Kara, A. (2018). Traversing cultural boundaries in IB: The complex relationships between explicit country and implicit cultural group boundaries at multiple levels. *Journal of International Business Studies*, *49*(8), 1081–1099.

Pezderka, N., & Sinkovics, R. R. (2011). A conceptualization of e-risk perceptions and implications for small firm active online internationalization. *International Business Review*, *20*(4), 409–422.

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, *63*(1), 539–569.

Ragin, C. C. (1987). *The comparative method: Moving beyond qualitative and quantitative strategies*. Berkeley: University of California Press.

Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond*. Chicago and London: University of Chicago Press.

Ranger-Moore, J. (1997). Bigger may be better, but is older wiser? Organizational age and size in the New York life insurance industry. *American Sociological Review*, *62*(6), 903–920.

Ravichandran, T., Han, S., & Mithas, S. (2017). Mitigating diminishing returns to R&D: The role of information technology in innovation. *Information Systems Research*, *28*(4), 812–827.

Reuschl, A. J., Deist, M. K., & Maalaoui, A. (2022). Digital transformation during a pandemic: Stretching the organizational elasticity. *Journal of Business Research*, *144*, 1320–1332.

Rindfleisch, A., O'Hern, M., & Sachdev, V. (2017). The digital revolution, 3D printing, and innovation as data. *Journal of Product Innovation Management*, *34*(5), 681–690.

Roberts, N., Galluch, P. S., Dinger, M., & Grover, V. (2012). Absorptive capacity and information systems research: Review, synthesis, and directions for future research. *MIS Quarterly*, *36*(2), 625–648.

Rothaermel, F. T., & Boeker, W. (2008). Old technology meets new technology: Complementarities, similarities, and alliance formation. *Strategic Management Journal*, *29*(1), 47–77.

Sarkar, M., Echambadi, R., Cavusgil, S. T., & Aulakh, P. S. (2001). The influence of complementarity, compatibility, and relationship capital on alliance performance. *Journal of the Academy of Marketing Science*, *29*(4), 358–373.

Sarmento, M., & Simões, C. (2018). The evolving role of trade fairs in business: A systematic literature review and a research agenda. *Industrial Marketing Management*, *73*, 154–170.

Schilling, M. A. (2009). Understanding the alliance data. *Strategic Management Journal*, *30*(3), 233–260.

Schneider, C. Q., & Wagemann, C. (2012). *Set-theoretic methods for the social sciences: A guide to qualitative comparative analysis*. Cambridge: Cambridge University Press.

Schotter, A., & Beamish, P. W. (2013). The hassle factor: An explanation for managerial location shunning. *Journal of International Business Studies*, *44*(5), 521–544.

Schwab, K., & Sala-i-Martín, X. (2016). *The global competitiveness report 2016–2017*. Geneva: World Economic Forum.

Setia, P., Venkatesh, V., & Joglekar, S. (2013). Leveraging digital technologies: How information quality leads to localized capabilities and customer service performance. *MIS Quarterly*, *37*(2), 565–590.

Shu, C., Jin, J. L., & Zhou, K. Z. (2017). A contingent view of partner coopetition in international joint ventures. *Journal of International Marketing*, *25*(3), 42–60.

Simonin, B. L. (1999). Ambiguity and the process of knowledge transfer in strategic alliances. *Strategic Management Journal*, *20*(7), 595–623.

Simonin, B. L. (2004). An empirical investigation of the process of knowledge transfer in international strategic alliances. *Journal of International Business Studies*, *35*(5), 407–427.

Sinkovics, N., Choksy, U. S., Sinkovics, R. R., & Mudambi, R. (2019). Knowledge connectivity in an adverse context: Global value chains and Pakistani offshore service providers. *Management International Review*, *59*(1), 131–170.

Sinkovics, N., Liu, C.-L., Sinkovics, R. R., & Mudambi, R. (2021). The dark side of trust in global value chains: Taiwan's electronics and IT hardware industries. *Journal of World Business*, *56*(4), 101195.

Sinkovics, N., Sinkovics, R. R., & Jean, R.-J. B. (2013). The internet as an alternative path to internationalization? *International Marketing Review*, *30*(2), 130–155.

Sinkovics, R. R., & Sinkovics, N. (2020). The Internet and international marketing—From trigger technology to platforms and new markets. *International Marketing Review*, *37*(3), 437–446.

Snow, C. C., Fjeldstad, Ø. D., & Langer, A. M. (2017). Designing the digital organization. *Journal of Organization Design*, *6*(1), 1–13.

Sørensen, J. B., & Stuart, T. E. (2000). Aging, obsolescence, and organizational innovation. *Administrative Science Quarterly*, *45*(1), 81–112.

Srikanth, K., & Puranam, P. (2011). Integrating distributed work: Comparing task design, communication, and tacit coordination mechanisms. *Strategic Management Journal*, *32*(8), 849–875.

Stahl, G. K., & Tung, R. L. (2015). Towards a more balanced treatment of culture in international business studies: The need for positive cross-cultural scholarship. *Journal of International Business Studies*, *46*(4), 391–414.

Steensma, H. K., Marino, L., Weaver, K. M., & Dickson, P. H. (2000). The influence of national culture on the formation of technology alliances by entrepreneurial firms. *Academy of Management Journal*, *43*(5), 951–973.

Szulanski, G. (1996). Exploring internal stickiness: Impediments to the transfer of best practice within the firm. *Strategic Management Journal*, *17*(S2), 27–43.

Tallman, S., Luo, Y., & Buckley, P. J. (2018). Business models in global competition. *Global Strategy Journal*, *8*(4), 517–535.

Täuscher, K., Bouncken, R., & Pesch, R. (2021). Gaining legitimacy by being different: Optimal distinctiveness in crowdfunding platforms. *Academy of Management Journal*, *64*(1), 149–179.

Tidström, A. (2014). Managing tensions in coopetition. *Industrial Marketing Management*, *43*(2), 261–271.

Tilson, D., Lyytinen, K., & Sørensen, C. (2010). Research commentary—Digital infrastructures: The missing IS research agenda. *Information Systems Research*, *21*(4), 748–759.

Toedtling, F., Grillitsch, M., & Hoeglinger, C. (2012). Knowledge sourcing and innovation in Austrian ICT companies—How does geography matter? *Industry and Innovation*, *19*(4), 327–348.

Toedtling, F., Lehner, P., & Trippl, M. (2006). Innovation in knowledge intensive industries: The nature and geography of knowledge links. *European Planning Studies*, *14*(8), 1035–1058.

Törnroos, J.-Å., Halinen, A., & Medlin, C. J. (2017). Dimensions of space in business network research. *Industrial Marketing Management*, *61*, 10–19.

Tung, R. L., & Verbeke, A. (2010). Beyond Hofstede and GLOBE: Improving the quality of cross-cultural research. *Journal of International Business Studies*, *41*(8), 1259–1274.

Turkina, E., & Van Assche, A. (2018). Global connectedness and local innovation in industrial clusters. *Journal of International Business Studies*, *49*(6), 706–728.

Turkina, E., Van Assche, A., & Kali, R. (2016). Structure and evolution of global cluster networks: Evidence from the aerospace industry. *Journal of Economic Geography*, *16*(6), 1211–1234.

Verbeke, A., Ciravegna, L., Lopez, L. E., & Kundu, S. K. (2019). Five configurations of opportunism in international market entry. *Journal of Management Studies*, *56*(7), 1287–1313.

Vis, B., & Dul, J. (2016). Analyzing relationships of necessity not just in kind but also in degree: Complementing fsQCA with NCA. *Sociological Methods & Research*, *47*(4), 872–899.

Wimelius, H., Mathiassen, L., Holmström, J., & Keil, M. (2021). A paradoxical perspective on technology renewal in digital transformation. *Information Systems Journal*, *31*(1), 198–225.

Yadav, N., Kumar, R., & Malik, A. (2022). Global developments in coopetition research: A bibliometric analysis of research articles published between 2010 and 2020. *Journal of Business Research*, *145*, 495–508.

Yamin, M., & Sinkovics, R. R. (2006). Online internationalisation, psychic distance reduction and the virtuality trap. *International Business Review*, *15*(4), 339–360.

Yan, Y., Dong, J. Q., & Faems, D. (2020). Not every coopetitor is the same: The impact of technological, market and geographical overlap with coopetitors on firms' breakthrough inventions. *Long Range Planning*, *53*(1), 101873.

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.

Zaheer, S., & Manrakhan, S. (2001). Concentration and dispersion in global industries: Remote electronic access and the location of economic activities. *Journal of International Business Studies*, *32*(4), 667–686.

Zaheer, S., Schomaker, M. S., & Nachum, L. (2012). Distance without direction: Restoring credibility to a much-loved construct. *Journal of International Business Studies*, *43*(1), 18–27.

Zhang, H., Zhou, M., Rao, H., & Zhou, D. (2021). Dynamic simulation research on the effect of resource heterogeneity on knowledge transfer in R&D alliances. *Knowledge Management Research & Practice*, *19*(3), 370–386.

How to cite this article: Bouncken, R. B., Fredrich, V., Sinkovics, N., & Sinkovics, R. R. (2023). Digitalization of cross-border R&D alliances: Configurational insights and cognitive digitalization biases. *Global Strategy Journal*, *13*(2), 281–314. https://doi.org/10.1002/gsj.1469

APPENDIX

REPRESENTATIVENESS OF PRIMARY ALLIANCE SAMPLE

Our primary alliance sample consists of $N = 298$ R&D alliances. Table A1 summarizes descriptive statistics and bivariate correlations of all *dyadic* R&D alliances. On average, these R&D alliances started 4.4 years ago (median = 3.2 years), and the geographic distance between collaborating firms' headquarters was 2485 km (479 km). The surveyed firms were established in 1981 (1991), employed a staff of 2719 (70), and achieved a 21% (15%) return on equity with annual sales of 630 M€ (13 M€). They spent 16% (10%) of their annual sales on R&D and filed

TABLE A1 Descriptive statistics and bivariate correlations

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	Relative absorptive capacity A	(0.93)	−0.08	0.03	0.02	−0.03	0.00	−0.03	0.02	0.05	−0.02	**0.14**	0.07	0.08	0.07	0.05	0.06	−0.04	−0.01	−0.05	−0.05	−0.02
2	Alliance-level digital technologies	−0.07	(1.00)	0.02	0.00	−0.06	0.01	−0.06	−0.04	−0.10	0.03	0.06	**0.15**	−0.04	**0.14**	0.07	−0.02	0.06	**0.18**	0.03	**0.15**	0.00
3	Relative firm sizes B/A	0.08	0.03	(0.89)	**0.60**	−0.02	−0.03	0.02	0.01	−0.02	**−0.20**	**−0.12**	**0.42**	0.09	**−0.13**	0.05	**−0.25**	**0.35**	**−0.39**	**−0.34**	**0.65**	**0.43**
4	Relative firm ages B/A	0.06	−0.01	**0.60**	(0.94)	0.06	0.07	0.08	0.07	0.02	**−0.12**	**−0.13**	**0.25**	0.05	−0.05	**0.12**	**−0.25**	**0.26**	**−0.32**	**−0.58**	**0.38**	**0.63**
5	Technological distance	−0.03	0.03	0.02	0.07	(0.67)	0.03	0.03	0.04	0.03	−0.11	**−0.29**	**−0.23**	−0.02	−0.10	0.03	**−0.48**	**−0.27**	**−0.28**	**−0.16**	**−0.18**	−0.03
6	Market distance	0.00	0.01	−0.05	0.07	**0.16**	(0.91)	0.05	0.05	0.08	−0.04	0.09	0.01	**−0.12**	**0.14**	0.07	0.04	0.01	0.00	−0.06	−0.04	0.01
7	Geographic distance	0.00	−0.07	−0.03	0.05	0.06	0.05	(0.74)	**0.70**	**0.73**	**0.18**	−0.02	0.09	0.07	−0.02	0.00	−0.07	−0.02	−0.04	**−0.12**	−0.05	−0.01
8	Cultural distance (9D values)	0.02	−0.04	−0.01	0.08	0.08	0.05	**0.65**	(0.96)	**0.70**	**0.22**	−0.06	0.04	0.08	−0.09	−0.07	−0.10	−0.07	−0.04	−0.09	−0.09	0.00
9	Cross-border alliance	0.05	−0.10	−0.04	0.01	0.07	**0.12**	**0.59**	**0.72**	(1.00)	0.11	−0.03	0.00	0.09	−0.05	−0.04	−0.08	−0.08	−0.03	−0.05	−0.07	−0.02
10	Inverse Mills ratio	−0.01	0.03	**−0.22**	**−0.17**	−0.01	−0.01	**0.22**	**0.27**	0.11	(1.00)	0.08	0.09	0.09	0.03	−0.07	0.09	−0.05	**0.51**	**0.17**	**0.15**	−0.04
11	% Digital intensity A pre	0.08	0.02	0.04	−0.01	**−0.14**	0.07	−0.01	−0.08	−0.03	−0.03	(0.47)	0.05	−0.03	**0.17**	0.06	**0.51**	−0.08	**0.30**	**0.18**	**0.15**	−0.01
12	% Digital intensity B pre	0.01	**0.16**	**0.24**	**0.12**	−0.08	−0.03	0.06	0.04	0.07	0.00	**0.16**	(0.39)	0.10	0.11	−0.06	**−0.13**	**0.56**	0.08	−0.10	**0.42**	**0.17**
13	Partner-specific alliance experience	0.06	−0.01	0.06	0.03	0.03	−0.08	0.03	0.09	0.06	**0.12**	−0.04	0.02	(0.83)	−0.03	**−0.14**	−0.02	−0.05	−0.03	0.03	0.00	0.05
14	General alliance experience A	0.05	**0.14**	**−0.16**	−0.06	0.01	0.15	−0.03	−0.08	−0.07	**0.12**	0.11	0.03	−0.01	(0.77)	0.05	0.10	0.00	**0.22**	0.09	0.06	0.01
15	% R&D intensity A	−0.05	0.08	0.01	**0.12**	−0.02	0.09	−0.05	−0.09	−0.07	−0.06	**0.14**	−0.05	−0.09	0.07	(0.66)	−0.02	−0.03	−0.10	**−0.26**	0.03	−0.09

(Continues)

TABLE A1 (Continued)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
16 Exploration A	0.05	−0.02	**−0.25**	**−0.26**	**−0.26**	0.04	−0.02	−0.11	−0.08	0.10	**0.30**	−0.08	−0.03	**0.13**	0.01	(0.99)	**−0.26**	**0.34**	**0.30**	−0.02	−0.04
17 Exploration B	−0.02	0.06	**0.36**	**0.27**	**−0.15**	−0.01	−0.05	−0.06	−0.09	−0.05	−0.06	**0.34**	−0.04	0.03	−0.07	**−0.26**	(0.99)	0.04	−0.09	**0.35**	**0.24**
18 Firm size A	−0.01	0.11	**−0.32**	**−0.13**	−0.07	0.07	0.02	0.00	−0.03	**0.23**	0.08	0.02	−0.07	**0.29**	−0.05	**0.16**	0.01	(0.06)	**0.49**	**0.23**	0.00
19 Firm age A	−0.03	0.04	**−0.25**	**−0.58**	−0.01	−0.07	−0.11	−0.11	−0.05	**0.14**	−0.01	−0.03	−0.01	**0.13**	**−0.18**	**0.30**	−0.02	**0.15**	(0.65)	−0.01	**0.14**
20 Firm size B	0.11	0.06	**0.50**	**0.28**	−0.03	0.04	0.00	−0.02	−0.02	0.03	0.04	**0.16**	−0.02	0.10	−0.04	−0.04	**0.18**	0.03	−0.04	(0.06)	**0.44**
21 Firm age B	0.05	−0.01	**0.38**	**0.56**	0.02	0.02	−0.02	0.04	−0.02	0.03	−0.04	0.05	0.08	0.09	−0.11	0.05	**0.24**	0.02	**0.16**	**0.29**	(0.62)
Mean	0.00	0.47	1.27	0.08	0.90	0.69	2.5 k	0.90	0.51	24.39	0.06	0.09	52.72	26.30	16.3	0.39	0.53	2.7 k	36.91	23.5 k	40.57
Standard deviation	0.92	0.50	3.21	1.09	0.16	0.28	3.7 k	1.24	0.50	44.57	0.18	0.19	41.18	32.73	18.9	0.42	0.42	13.3 k	33.49	82.5 k	35.94
Minimum	−2.47	0	−9.51	−3.57	0.00	0.00	1	0.00	0.00	0.67	0.00	0.00	0	0	0.00	0.00	0.00	1	1	2	0
Maximum	1.30	1	11.65	2.90	1.00	1.00	17.0 k	4.91	1.00	526.0	1.00	1.00	180	117	100.0	0.98	0.99	140 k	170	617 k	178

Note: $N = 292$ dyadic R&D alliances; significant Pearson correlations are bold (p-value $\leq .05$); k = in thousands; raw data below and calibrated data above diagonal, shared variances in brackets on diagonal indicate how much variance (= 1 − shared variance) is neglected due to calibration.

TABLE A2 Comparison of SDC versus our primary alliance data

Source	SDC secondary database		Primary database	
Number of R&D alliances	17,519		298	
% cross-border	54.1%		51.0%	
Years of announcement/ start	1973–2018		1999–2018	
% dyadic alliances	15,882 (90.7%)		292 (98.0%)	
All subsequent statistics for a subsample of dyadic alliances				
Mean (median) alliance length	4.7 (3.0) years (known for 6.1%[a])		4.5 (4.0) years (known for 4.5%)	
Number of unique 2-digit SIC codes ($Blau_N$)	74 (0.81)		51 (0.92)	
Top3 2-digit SIC codes (%)	1st: 87 (35.7%) 2nd: 28 (16.0%) 3rd: 73 (14.1%)		1st: 38 (14.6%) 2nd: 36 (13.7%) 3rd: 87 (10.6%)	
% ordinal 4-digit SIC-code similarity ($Blau_N$)	No overlap: 49.5% 1st digit: 11.2% 2nd digit: 6.7% 3rd digit: 13.3% 4th digit: 19.2% (0.68)		No overlap: 48.6% 1st digit: 20.5% 2nd digit: 8.6% 3rd digit: 6.2% 4th digit: 16.1% (0.69)	
Firm of the dyad	Firm A	Firm B	Firm A	Firm B
Mean (median) year of foundation	1976 (1993)	1979 (1996)	1981 (1991)	1977 (1989)
Mean (median) number of employees	38,927 (5301)	45,486 (10,500)	2719 (70)	23,468 (200)
% SMEs (≤500)	27.9%	19.8%	80.5%	63.7%
Number of countries ($Blau_N$)	85 (0.62)	93 (0.67)	33 (0.74)	36 (0.80)
% Top3 countries	1st: 60.1%, USA 2nd: 8.9%, Japan 3rd: 4.8%, UK	1st: 56.3%, USA 2nd: 9.2%, Japan 3rd: 5.1%, UK	1st: 49.0%, Germany 2nd: 6.5%, USA 3rd: 6.5%, China	1st: 42.5%, Germany 2nd: 11.6%, USA 3rd: 5.5%, China
Mean (median) number of patents 5 years pre-alliance[b]	368 (21)	385 (20)	114 (1)	795 (2)
	10% (4%)	10% (3%)	7% (0%)	14% (3%)

(Continues)

TABLE A2 (Continued)

Source	SDC secondary database	Primary database
Mean (median) % digital patents[b]		
Mean (median) geographic distance between firms	3978 km (1161 km)	2485 km (479 km)
Mean (median) Hofstede's 4D-distance[c]	2.23 (2.32)	1.91 (1.64)
Mean (median) Globe's values 9D-distance[c]	2.07 (2.16)	1.78 (1.48)
Mean (median) Globe's practices 9D-distance[c]	2.35 (2.05)	2.04 (1.75)

[a]Mostly only date of announcement reported here: actual (1.4%) or original length (4.8%) or an average of both (0.1%).
[b]Random sample of 500 SDC alliances announced after 1999 versus all primary alliances.
[c]Cultural distances for cross-border subsamples.

114 patents (1 patent) in the past 5 years. Their dyadic alliance partners were established in 1977 (1989), employed a staff of 23,468 (200), and achieved a 17% (14%) return on equity with annual sales of 10,428 M€ (56 M€). These considerably bigger partners filed 795 patents (2 patents) in the past 5 years before alliance formation according to the largest public database on the internet, Espacenet of the European Patent Office (https://worldwide.espacenet.com/), which covers over 120 million patent documents from more than 90 countries. We further applied textual analysis and screened all identified patent documents for the word "digital" (search string: ftxt = "digital*"). Responding firms' patents contained 7% (0%) of "digital" wording; their bigger partners were significantly more digital: 14% (3%).

Table A2 compares descriptive statistics of selected country-, industry-, firm-, and alliance-level characteristics of all 17,519 R&D alliances in the world's largest alliance database, Securities Data Company SDC Platinum (Schilling, 2009), with our primary data. Only 9.3% of all R&D alliances are multi-partner alliances and there are increasingly more dyadic cross-border R&D alliances between geographically and culturally distant countries over time (N = 17,519 over 1973–2018: Pearson-rho with time horizon: % dyadic: $r = 0.06$, $p < .001$; number of participants: $r = -0.06$, $p < .001$, % international: $r = 0.12$, $p < .001$, geographic distance in km: $r = 0.06$, $p < .001$, Globe 9D values: $r = 0.12$, $p < .001$; *pre*-2010: 90% dyadic, 46% international, 2.2 participants, 3862 km, 0.92 Globe 9D values versus *post*-2010: 93% dyadic, 58% international, 2.1 participants, 4307 km, 1.31 Globe 9D values). Firms established dyadic R&D alliances mostly for engineering and management services (SIC 87 = 35.7%), whereas our primary R&D alliances mostly represent the development of instruments and related products (SIC

38 = 14.6%). The greatest difference between both databases concerns firm size: SDC mostly reports dyadic R&D alliances between big firms (39% involved at least one SME, only 5% both SMEs), whereas our primary data are closer to a true representation of most economies, mainly consisting of SMEs (with 90% of all dyadic R&D alliances involving at least one SME, 54% both SMEs). Moreover, the bigger SDC firms filed patents more frequently (median numbers: 20–21 vs. 1–2).

POST HOC ANALYSIS

Several additional post hoc tests indicate the sensitivity of our findings. First, we applied configurational analysis on the national ($N = 144$) subsample. This reduced the number of conditions to six due to the non-existent cultural distance in the national subsample. Table A3 shows that the high ACap in national R&D alliances is characterized by low technological distance in a non-digital alliance setting. Path *high 1b* and the paths *low 2d* and *low 2e* only differ in their relative firm demographics. The high market distance limits the ability to absorb knowledge from bigger and older partners despite the technological similarity. Path *high 1a* characterizes traditional coopetition alliances. Geographic distance (*high 1c*) can be mitigated in the presence of digital technologies. Digital technologies characterize dysfunctional national R&D alliances without technological overlap (*low 2a*, *2b*, *2c*).

Second, we tested alternative theoretically driven context variables to account for the greater complexity of cross-border R&D alliances relative to their national counterparts (Oxley & Sampson, 2004). In line with this, we excluded the four dyadic alliance-level distances and illuminated alternative firm- and alliance-level conditions (e.g., "experience"-model, "exploration"-model, "digital intensity"-model). These patterns were too complex or inconsistent, highlighting relative ACap as an alliance-level phenomenon (Lane & Lubatkin, 1998).

TABLE A3 Configurations for achieving (1) high versus (2) low ACap in national R&D alliances

N≥1; C≥0.85	(1) High ACap			(2) Low ACap				
	1a	1b	1c	2a	2b	2c	2d	2e
Alliance infrastructure								
1) Digital technologies	⊗	⊗	•	●	●	●	⨂	⨂
Firm characteristics								
2) Relatively bigger partner firm		⊗	•	⨂	⨂	•	●	•
3) Relatively older partner firm	•	⊗	•			•	•	●
Dyadic distances								
4) Technological distance	⊗	⊗	⊗	●	●	●	⨂	⨂
5) Market distance	⊗	•	⊗	⊗		•	●	●
6) Geographic distance	⊗	⊗	•		⊗	●	⊗	⊗
Consistency	0.87	0.90	0.86	0.89 (0.84)	0.85 (0.84)	0.91 (0.91)	0.93 (0.85)	0.93 (0.91)
Raw coverage	0.06	0.04	0.03	0.16 (0.23)	0.23 (0.23)	0.11 (0.15)	0.06 (0.07)	0.06 (0.06)
Unique coverage	0.03	0.02	0.03	0.00 (0.15)	0.07 (0.15)	0.05 (0.06)	0.06 (0.00)	0.06 (0.00)
Overall solution consistency		**0.87**				**0.87 (0.85)**		
Overall solution coverage		**0.11**				**0.34 (0.36)**		

Note: Black circles indicate the presence, crossed white circles indicate the negation, and blank spaces signify the absence of a causal condition. Big circles indicate parsimonious solutions with fit evaluation in parentheses.

Third, we complemented the correlational analysis by running a traditional multivariate linear regression analysis and yielded no significant (all β_{linear} with $p > .10$) "net effects" (Ragin, 2008) in the total sample and the cross-border subsample. Only two significant direct effects emerged in the *national* subsample. On the one hand, alliance-level digital technologies represent a barrier to ACap ($\beta_{\text{nat}} = -0.18$, $p = .051$ vs. $\beta_{\text{int}} = 0.01$, $p = .913$). This marginal net effect is supported in the calibrated national subsample (cf. Table 1: $r_{\text{nat}} = -0.16$, $p = .052$). On the other hand, firm-level digital intensity of responding firms fosters ACap ($\beta_{\text{nat}} = 0.24$, $p = .025$ vs. $\beta_{\text{int}} = -0.00$, $p = .983$). These results remained robust using non-parametric bootstrapping with 5000 bias-corrected re-samples. Furthermore, we relaxed the linearity assumption by estimating quadratic parameters for all quantitative conditions (Ganzach, 1998). These parameters showed no significance ($\Delta R^2 = 0.059$, $p = .465$, all $\beta_{\text{quadratic}}$ with $p > .10$).

Fourth, to better understand the negative association of digital technologies in national R&D alliances, we tested single digital technologies instead of an "OR"-conjunction. None of the unique digital technologies ($p > .10$) reduced absorptive capacity, indicating an aggregated higher-order reservation vis-à-vis digital technologies. Similarly, the dominant condition of present digital technologies in dysfunctional cross-border and national fsQCA-based configurations became inconsistent when focusing on unique technologies. Notably, unique technologies lacked substantial sample sizes (with a maximum of 15%).

Fifth, when dealing with cultural distance as a country-level distance, we tried alternative operationalizations and Globe's 9-dimensional *value*-based version yielded the greatest correlation with perceived cultural distance in a small international subsample where this perceived measure was part of the survey ($N = 45$: $r_{\text{values}} = 0.50$, $p < .001$, $r_{\text{practices}} = 0.33$, $p = .027$, $r_{\text{Hofstede}} = 0.22$, $p = .147$), further externally validating our choice. A composite-based factor of all three cultural distances (with AVE = 0.68) yielded the same cross-border configurations. Following the more recent distinction between *in-kind* versus *in-degree necessity* (Vis & Dul, 2016), we applied *necessary condition analysis* (NCA) (Dul, 2016, 2019) for a series of additional country-level measures. Berry et al. (2010) suggested objective proxies for country-level knowledge distance, financial distance, economic distance, political distance, global connectedness distance, and demographical distance. Moreover, we added language distance (Eberhard et al., 2020) as a barrier to learning in general and the annually adjusted 12 pillars of global competitiveness (Schwab & Sala-i-Martín, 2016). None of these country-level conditions yielded the consistency threshold for general necessity (consistency <0.90) nor in-degree necessity ($d < 0.10$ and $p > .10$; Dul, 2019).

Sixth, we tried alternative settings in the calibration (e.g., ACap scores at ± 2 for full-out and full-in membership) and selection (e.g., consistency 0.80–0.90, $N \geq 2$) in line with the well-known sensitivity of configurational results (Krogslund et al., 2015). These iterations produced additional paths but essentially replicated our core findings.

Last, we assessed the consequences of alliance-level digital technologies and relative ACap for unintended alliance termination (i.e., binary alliance failure) for a subsample of all R&D alliances 2 years after the survey ($N = 151$ with 11, i.e., 7% failed alliances; $N_{\text{int}} = 81$ with 4, i.e., 5% failed alliances; $N_{\text{nat}} = 70$ with 7, i.e., 10% failed alliances). Most interestingly, both relative ACap and alliance-level digital technologies reduced alliance failure only in *national* R&D alliances (national: $r_{\text{ACap}} = -0.22$, $p = .063$, $r_{\text{DIGI}} = -0.25$, $p = .039$; international: $r_{\text{ACap}} = -0.03$, $p = .793$, $r_{\text{DIGI}} = 0.03$, $p = .782$).