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Configuring alliance portfolios for digital innovation

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ABSTRACT

We examine how firms configure alliance portfolios—that is, networks of partnering firms—in order to exchange, share, or codevelop the capabilities they require to engage in digital innovation. We analyze data from 550 U.S. firms and the strategic alliances they formed within and across industrial sectors to study how the configuration of alliance portfolios in terms of size, degree of exploration, internationality, and competition affects the volume and quality of digital patents. We find that alliances appear to be an effective means, yet alliances for digital innovations require a different configuration when compared with alliances for non-digital innovations. Large and explorative alliance portfolios help with the creation of digital innovations while international alliances and alliances involving competitors do not. We discuss the implications of these findings for research on digital innovation and alliances. We also distill practical advice to executives charged with making strategic decisions about inter-firm partnerships.

Introduction

Creating and managing digital innovations—that is, new product or service offerings enabled or embodied by digital technologies that create value in novel ways (Hund et al., 2021; Yoo et al., 2010)—is notoriously challenging for incumbent firms (Chanias et al., 2019; Oberländer et al., 2021; Svahn et al., 2017). This is because the “emerging digital innovation regime” differs fundamentally from the modular and industrial innovation regimes that defined innovation and competition for most of the 20th century (Lyytinen, 2022). Digital innovation requires new capabilities that revolve around the ongoing development of representations of real-world phenomena in digital form, the integration of these representations across a variety of hardware and software devices, and their embodiment in organizational settings to give them purpose and meaning (Lyytinen, 2022; Svahn et al., 2017).

How do incumbent firms acquire these new capabilities, especially when mergers and acquisitions are not feasible (Hanelt et al., 2021), interfacing with platforms is not possible (Hodapp & Hanelt, 2022), and collaboration communities are too difficult to build (von Briel & Recker, 2017)? Strategic management literature suggests that alliances could be an effective alternative. *Alliances* are networks of two or more firms that exchange, share, or codevelop resources or capabilities to achieve mutually beneficial outcomes without equity investment (Koza & Lewin, 1998; Wassmer, 2010). They facilitate inter-firm knowledge transfer (e.g., Inkpen, 1998; Lavie et al., 2010) and contribute to a firm’s ability to innovate (e.g., Duysters & Lokshin, 2011). And indeed, several recent industry

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developments suggest that alliances are seen as a promising strategic option for digital innovation. For example, together with Huawei, the United Nations Industrial Development Organization created the "Global Alliance on Artificial Intelligence for Industry and Manufacturing" (https://aim.unido.org/) in 2023 to jointly promote the innovative application of AI technologies. As another example, C3 AI, Baker Hughes, Microsoft, and Shell launched the Open AI Energy Initiative (OAI) and developed an open framework as the foundation of an AI solutions ecosystem that seeks to transform the energy industry (https://www.bakerhughes.com/ai-bakerhughesc3ai). As these examples show, alliances foster digital innovations by facilitating the generation and integration of knowledge and resources necessary for bridging the gap between existing and required capabilities within incumbent firms (Chanias et al., 2019; Svahn et al., 2017). Yet, how incumbent firms should configure a portfolio of alliances for creating digital innovations remains poorly understood.

In this paper, we examine the impact of alliance portfolio configurations on the ability of firms to create digital innovations. This relationship presents a complex dynamic. On the one hand, alliances heavily rely on cooperation, agreement, and alignment among a select group of partners, which explains why alliance portfolios often consist of trusted firms operating within similar industries in geographically bound contexts (Cooke, 2001; Das & Teng, 2000; Wassmer, 2010). On the other hand, digital innovations are semiotic, open-ended, and inherently modular in nature (Hund et al., 2021; Lyytinen, 2022; Yoo et al., 2010). As a result, they engender an organizing logic that favors collaboration between a larger and more diverse set of heterogeneous actors (Dhanaraj & Parkhe, 2006; Majchrzak & Malhotra, 2013; Nambisan et al., 2017).

To unpack this complex relationship, we empirically analyze and theorize how the configuration of an alliance portfolio in terms of size, degree of exploration, internationality, and competition impacts the creation of digital innovations.[1] We ask: *How do configurations of alliance portfolios relate to the creation of digital innovations in incumbent firms?*

To answer this question, we drew on patent data from the United States Patent and Trademark Office (USPTO), which we merged with alliance and financial data from publicly listed U.S.-based firms spanning thirteen years of observation. Our analysis suggests three key findings. First, alliances can be an effective vehicle for incumbent firms to engage in digital innovation, but they need to be constructed differently from alliances for non-digital innovation. Second, larger alliance portfolios and alliances that are configured with a higher degree in exploration are positively associated with the creation of digital innovations. Third, high degrees of internationality and competition between firms entering alliances show adverse effects.

Our research makes several contributions. To scholars interested in information systems strategy, we show that inter-firm links created through alliances can help firms to not only yield more but also higher quality digital innovations. To scholars interested in alliances, we uncover nuances in how an alliance portfolio should be configured for digital as opposed to non-digital innovation. For practitioners, we provide advice about how firms can go about constructing effective alliances with partner firms within and beyond their specific industry.

Background

How digital innovation differs from non-digital innovation

Digital innovation has gained immense strategic importance for how firms create and appropriate value (Autio et al., 2021; Chanias et al., 2019). For instance, digital innovation has led to the creation of entirely new product categories, from wearables and smartphones to entertainment media and augmented reality applications (Hylving & Schultze, 2020; Lyytinen, 2022), as well as new digital service offerings in areas such as administration (Lyytinen & Rose, 2003), hospitality (Orlikowski & Scott, 2015) and healthcare (Oborn et al., 2021). Digital innovation has also spawned new business models (Böttcher et al., 2022; Oberländer et al., 2021) and even transformed entire markets and industries (Autio et al., 2021; Hendershott et al., 2021).

Digital innovations exhibit three fundamental properties that set them apart from the industrial-age, i.e., from non-digital innovations that have been the focus of most innovation studies prior the advent of digital technology (Baiyere et al., 2023; Lyytinen, 2022; Yoo et al., 2010). First, digital innovations are semiotic (Yoo, 2010), meaning that their components and interactions are represented in digitized, binary form – as 0's and 1's. These homogenized digital representations are re-programmable; they can be infused with new meaning and made to fit new purposes and use cases (Wang et al., 2022). Second, digital innovations are inherently modular, which enables them to be ever-incomplete, meaning they can be expanded and revised both during design and use (Henfridsson et al., 2018; Lehmann & Recker, 2022). Third, digital innovations are open. Individual components of digital innovations can contribute to a variety of product architectures across institutional contexts (Nambisan et al., 2017). Consider the variety of use cases of Google Maps, an innovation that builds upon digital representations in modules such as geo-locations and routing, among others; Google Maps can be used as a navigation app, but also within ride-sharing apps such as Gojek, and even as part of games such as Pokémon Go. Collectively, these three properties of digital innovations have profound implications for how incumbent firms should configure alliance portfolios, in that they urge us to revisit assumptions about alliances as a vehicle for innovation.

Alliance portfolio configurations for digital innovations

Alliances emerge when two or more firms collaborate to realize a set of common goals or solve problems without substantial equity

[1] In this paper, we understand digital innovations as the development and filing of new patent applications with digital technologies at their core (Boudreau et al., 2022; Hanelt et al., 2021; Nylund & Brem, 2022; Zapadka et al., 2022).

investment (Inkpen, 1998; Wassmer, 2010). A defining characteristic of alliances is their focus on the cocreation and exchange of knowledge, which involves each party investing their resources in complementary ways (Das & Teng, 2000; Inkpen, 1998). Past research identifies at least two ways in which alliances aid innovation. First, alliances facilitate knowledge transfer between firms with complementary skills and resources (Inkpen, 1998). Second, as opposed to formal contracts or buyer–supplier relationships, alliances are essentially a dynamic and incomplete agreement (Anand & Khanna, 2000; Koza & Lewin, 1998) that provide partnering firms not only with access to resources but also necessary latitude and ambiguity to react to unanticipated changes as they arise.[2]

While these aspects are likely also relevant to digital innovation where both processes and outcomes of innovation are emergent and generative and can often not be specified ex-ante (Jarvenpaa & Standaert, 2018; Nambisan et al., 2017), exactly how alliances should be configured for creating digital innovations remains unclear. This is because the properties of digital innovations—semiotic, inherently modular, and open—may challenge assumptions underlying existing research about relevant alliance characteristics (see Table 1). Specifically, we identify-four characteristics of alliance portfolios that are potentially affected by digital innovation properties: portfolio size, degree of exploration, internationality, and competition.

Alliance portfolio size

The size of an alliance portfolio is an important strategic consideration in digital innovation because "successful digital innovation [inherently] depends on how [multiple] actors come to understand, share with others, and then modify their understandings of innovation outcomes, processes, and related markets" (Nambisan et al., 2017, p. 229). Digital innovation's inherently modular architecture may have implications for the optimal overall size of alliance portfolios. On the one hand, larger alliance portfolios increase the number of possible combinations in joint problem–solution pairing (Nambisan & Sawhney, 2011), which is also central to digital innovation (Lyytinen, 2022). It is known that larger alliance portfolios typically provide more resources that parties can draw from in innovation (Hoffmann, 2007; Lavie, 2007), a larger number of innovation opportunities (Shi et al., 2012), and better protection against the risk of individual alliances failing (Hoffmann, 2007; Lahiri & Narayanan, 2013). On the other hand, larger portfolios of alliances also increase complexity (Phene & Tallman, 2012), coordination costs (Jiang et al., 2010), and appropriation concerns (Gulati & Singh, 1998). Firms must invest the effort to govern large alliance portfolios and the resource and learning benefits that could be made available. In the context of digital innovation, it is thus unclear whether larger alliance portfolios are beneficial.

Alliance portfolio degree of exploration

Alliances also play an important role in the generation of new capabilities and resources needed for digital innovation. To that end, firms can either forge alliances within their existing network, that is, exploitative alliances, or engage with new and diverse firms, that is, explorative alliances (Connelly et al., 2019; Majchrzak & Malhotra, 2013; Teubner & Stockhinger, 2020). Exploitative alliances can be effective because they allow leveraging existing competencies with complementary capabilities by other firms (Yamakawa et al., 2011). Also, exploitative alliances often engender high trust and established social context, which can positively affect innovation (Gulati, 1995; Wassmer, 2010).

However, because digital innovations' inherent openness facilitates the integration of a vast range of agnostic digital technology components during design and use (Henfridsson et al., 2018; Lyytinen, 2022; Yoo et al., 2010), explorative alliances (those featuring a substantial share of previously unassociated partners) may be more effective because they provide access to new resources and insights into technologies, markets, and processes (Connelly et al., 2019; Duysters & Lokshin, 2011). Explorative alliance portfolios in the context of digital innovation may also lead to faster and more effective co-creation, in that they consider a broader range of digital innovation opportunities (Teubner & Stockhinger, 2020). Moreover, since digital innovation's modular architecture is particularly amenable to the recombination of existing and novel resources, explorative alliance portfolios might bring more and more diverse inputs, in turn increasing the possibilities to develop something new. Taken together, explorative alliance portfolios may be beneficial for creating digital innovations. Whether this is the case, however, remains unclear.

Alliance portfolio degree of internationality

The degree of internationality of alliances is a third strategic choice firms must decide upon when engaging in digital innovation. Because digital innovations are semiotic, meaning they rely on the representation of real-world phenomena as strings of 0's and 1's, expanding alliance portfolios internationally may be beneficial (Autio et al., 2021; Nambisan, 2020). Specifically, digital components are agnostic to sociocultural and geographic contexts if there is consensus about what the 0's and 1's represent. This property may simplify the integration of new, locally-unavailable resources or knowledge through alliances (Contractor et al., 2003) and present expansion opportunities into new markets (Inkpen, 1998). For example, in technology innovations, partnering with firms established in different geographical technology hubs is a promising strategy because of their knowledge of advanced technologies and local access to resources (Zhang et al., 2010).

At the same time, the semiotic nature of digital innovations may also amplify cultural differences. Whereas digital technology components are in principle agnostic and context-free, digital innovations themselves must still be embedded into local contexts (Lyytinen, 2022), which may lead to misalignment with local conditions, as was the case when OpenAI launched ChatGPT in Italy where local data-protection authorities initially banned access over privacy concerns. Establishing a shared understanding can be more

[2] Alliances are subject to uncertainties that are difficult to predict yet, affect the potential outcomes of alliance partnerships (Anand & Khanna, 2000). Contingencies include changes in the macroeconomic environment, competitive shifts among the partners involved, new market opportunities, and changing technologies.

Table 1
Alliance portfolio configuration's relevance to digital and non-digital innovation.

Alliance portfolio characteristics	Relevance to digital and non-digital innovation	
	Regular, non-digital innovations	Qualitative difference in digital innovations
Alliance portfolio size	More alliance partners may be associated with more resources that can be combined for innovation (e.g., Hoffmann, 2007). However, tightly integrated, and non-modular innovation architectures imply that coordination and integration requirements grow with an increasing number of contributions.	The semiotic and modular nature of digital innovations mean an increasing number of actors can be enabled to contribute to new digital innovations (e.g., Yoo et al., 2010).
Alliance portfolio degree of exploration	New partners add different knowledge and perspectives to benefit the creation of innovations, but an increasing number of new alliance partners also increases the complexity of cocreating something new (e.g., Duysters & Lokshin, 2011).	The openness of digital innovations means that new partner contributions can be made accessible and coupled fast and meaningfully to produce digital innovations through recombination (e.g., Baiyere et al., 2023; Henfridsson & Bygstad, 2013).
Alliance portfolio degree of internationality	International alliance partners add more diverse and market-specific knowledge to the alliance portfolio, but cultural and language differences create barriers to working together effectively (e.g., Contractor et al., 2003; Lavie et al., 2010).	The semiotic nature of digital innovation means international actors can easily contribute to the same digital innovation because digitalized bitstrings that are stored in a homogenized electronic format can be accessed and modified by any computing device irrespective of language and culture (e.g., Lyytinen, 2022).
Alliance portfolio degree of competition	Shared understanding and terminology of same-industry alliance partners may involve less-complex communication benefiting incremental innovations, but a lack of diversity also decreases creativity to co-create innovations (e.g., Luo et al., 2007). Also, winner-takes-all dynamics can put companies at a disadvantage when they collaborate with a competitor (e.g., Lyytinen et al., 2016).	The openness of digital innovation implies an agnostic nature (e.g., Yoo et al. 2010), which can lead to industry convergence but also temporary links between same-industry competitors.

costly or even impossible when the role of digital innovations in business and everyday life varies between international partners (Nambisan, 2020) or when sociocultural differences prevail (Baskerville et al., 2020; Faulkner & Runde, 2019). Moreover, local, regulatory requirements, consumer preferences, and the form of digital infrastructure and digital sovereignty across countries can render the development of digital innovations that would benefit partners equally more complex (Contractor et al., 2003; Nambisan, 2020). As such, less international alliances may have advantages in the context of digital innovations (Lavie et al., 2010; Nambisan, 2020). Taken together, it is unclear whether international alliance portfolios are beneficial for digital innovation.

Alliance portfolio degree of competition

Finally, the degree of competition between alliance partners may affect a firm's ability to create digital innovations. Digital innovation's openness enables the convergence of industries as well as temporary bindings between individual same-industry firms (Parker et al., 2017; Yoo et al., 2012). Therefore, alliances that include competitors may benefit from the joint creation of digital innovations. In such instances, alliances between competitors ensure the applicability of knowledge and resources to the problems partners seek to solve through digital innovations. A shared understanding leads to less-complex communication between alliance partners. The creation of digital innovations takes less time and the resulting digital innovations may prove to be more effective solutions to the problems the alliance sought to address (Luo et al., 2007; Ritala et al., 2008).

However, same-industry partners are associated with fewer complementary insights and less technological diversity, thus limiting the ability to create digital innovations (Connelly et al., 2019). In addition, alliances between competing firms may be susceptible to opportunistic behavior, which can threaten successful co-creation (Luo et al., 2007; Nakos et al., 2014). A key challenge in alliances between competing firms therefore lies in protecting digital innovation's openness for all actors' contributions, securing access to resources, predicated on the establishment of trust. In alliances with a high degree of competition, trust and cognitive agreement can be limited by rivalry and diverging objectives, and therefore knowledge and capabilities may not be shared equally (Nakos et al., 2014). Hence, the literature does not yet provide a clear recommendation regarding alliance configuration for digital innovation regarding the alliance's degree of competition.

Method

Research strategy and data

To unpack the complex relationship between alliance portfolio configuration and digital innovation, we developed a comprehensive panel dataset of all U.S. firms included in the Standard and Poor's (S&P) 500 index between 2006 and 2018. It includes patent data from the U.S. Patent Office, alliance data from the SDC Platinum database, and firm-level financial data (plus other control data) from Compustat.

Given the lack of a unique identifier across all three databases, we used a name-matching algorithm to link the data. We matched the assignee firms named in the patent databases to firms listed in the S&P Compustat North America database through a fuzzy name-matching algorithm implemented in Alteryx (Baruti, 2017). The algorithm measures the semantic similarity using the Jaro-Winkler distance (Winkler, 1990) with a default value of 0.8, which allowed us to account for differences in company name spelling and the use of associated legal entities (e.g., subsidiary firms) as assignees, and to add Compustat's global company key (gvkey) as a firm identifier. We validated our name-matching algorithm in comparison to prior patent data research (Hall et al., 2005; Stoffman et al., 2022). Additionally, we manually inspected the non-matching results to improve the fuzzy matching until we exceeded 90 % of fitting matches in the dataset. We also matched alliance data from the SDC Platinum database representing alliance deals for the respective years to the Compustat dataset using the shared cusip identifier.

Combining these three panel datasets, our final sample consisted of 478,154 patents assigned to 327 firms with 8.2 million forward citations of those patents during our 13-year period from 2006 to 2018. After merging all datasets and excluding missing data, we obtained 1,387 firm-year observations. We estimated a variety of models to examine different alliance portfolio configurations and estimate their impact on the volume and quality of digital patents. Next, we explain our variables (see Table 2) and our model identification strategies.

Dependent variables: volume and quality of digital patents

Firms frequently report digital innovations in the form of patent applications (e.g., Boudreau et al., 2022; Choi et al., 2021; Chung et al., 2019; Hanelt et al., 2021; Kohli & Melville, 2019; Nylund & Brem, 2022) because patenting allows firms to legally protect their innovations (Chung et al., 2019; Rahmati et al., 2021). Similar to others (Boudreau et al., 2022; Hanelt et al., 2021; Nylund & Brem, 2022; Rahmati et al., 2021; Zapadka et al., 2022), we consider patents as *digital* if a documented innovation involves digital technologies at its core for enablement or embodiment (e.g., new product or service offerings, methods, components, algorithms, or electronics). Previous studies involving digital patents typically referred only to the technological outcome of the innovation capability that is a new digital product offering (such as new content, a new algorithm, or a new application). However, digital patents also often stipulate novel procedures that involve digital technologies relevant for innovation, that is, for the development of new products and services. To illustrate, consider a digital software patent that we included in our analysis, created by Honda Motor Co., an original equipment manufacturer. They filed a patent in 2017 (patent reference: US10000153) both for its system for object indication on a vehicle display (a product) and a method for using this system (a process). Such patents that refer to digital innovations in both processes and products are common in the automotive industry (Lee & Berente, 2012), as well as in other supply chain processes (Gawer, 2009). Therefore, we decided to apply a broad understanding of digital patents that encompasses both types of digital innovation, which are usually closely interdependent (Nambisan et al., 2017).

We collected patent data in November 2022 from the PatentsView database provided by the USPTO for our dependent variables. We included in our patent dataset data from 2006 to 2018 because 80 % of patent applications are granted within four years (Hall et al., 2001). To account for the delay between application and granting (recent applications are potentially not cited, yet), we ended our sampling timeframe four years before our actual collection date. We also included forward citations for all patents for the respective years in our sample.

We first filtered for *utility patents*,[3] and then examined their position in the official Cooperative Patent Classification (CPC) scheme (USPTO, 2023). We used the two main groupings of the CPC structure (sections and classes) to construct a binary indicator to determine whether each patent specifies a digital innovation. We identified eight sections and subclasses of patents as containing digital innovations: namely G06 (Computing; Calculating; Counting), G07 (Checking Devices), G08 (Signaling), G09 (Education; Cryptography; Display; Advertising; Seals), G11 (Information Storage), G16 (Information and Communication Technology specially adapted for specific applications), H04 (Electrical Communication Techniques), and Y04 (Information or Communication Technologies affecting other technology areas).

We make three notes about our operationalization. First, we use the CPC codes (USPTO, 2023) instead of the International Patent Classification scheme (e.g., Choi et al., 2021; Chung et al., 2019) or the Espacenet scheme by the European Patent Office (Hanelt et al., 2021). CPC is a new global patent classification scheme jointly managed by European and U.S. Patent Offices and the U.S. Trademark Office. Second, we investigate patents that are enabled by or embodied in digital technology broadly (e.g., Hanelt et al., 2021; Nylund & Brem, 2022) rather than software patents (e.g., Boudreau et al., 2022; Chung et al., 2019; Hall & MacGarvie, 2010) or IT patents (e.g., Choi et al., 2021) specifically. Third, we deliberately construed an inclusive rather than exclusive operationalization of digital patents, because we aimed to minimize type-1 errors (missing digital innovations that should have been included in our sample). To explore the validity of this assumption, in our robustness analysis, we also tested for type-2 errors by applying a categorization of digital patents with a more narrow focus (Braun et al., 2011). We then constructed two main dependent variables: digital patent volume and digital patent quality.

Digital patent volume. We defined *digital patent volume* as the number of digital patents created by a firm within a specific year. For each year, we computed the volume of all digital patents applied for by a firm. For a given firm, we counted the number of patents classified as "digital" as per our definition (see Table 2) for each of the years in our sample. The mean score for digital patent volume in

[3] Patents "[that] may be granted to anyone who invents or discovers any new, useful, and nonobvious process, machine, article of manufacture, or composition of matter, or any new and useful improvement thereof (MPEP § 201)" (USPTO, 2023).

Table 2
Variable definitions, source databases, and references.

Variable	Operationalization	Database (Source)	Reference
Digital patent volume	The number of digital patents created by a firm within a specific year.	PatentsView (USPTO)	e.g., Hanelt et al., 2021; Nylund & Brem, 2022
Digital patent quality	The number of digital patents' forward citations appearing in subsequent patents corrected by patent age for a given year.	PatentsView (USPTO)	Hall et al., 2005
Alliance portfolio size	The number of newly entered alliances a focal firm engaged in during a particular year.	SDC Platinum	e.g., Lahiri & Narayanan, 2013; Wassmer et al., 2017
Alliance portfolio degree of exploration	The count of new partners (those with whom the firm has not previously been engaged) for any given year over the total number of all partners in the respective year.	SDC Platinum	Lin et al., 2007
Alliance portfolio degree of internationality	The number of international partners over the sum of all partners within a network for a given year.	SDC Platinum	Lavie & Miller, 2008
Alliance portfolio degree of competition	The ratio of matches between a focal firm's primary industry segment and its partners' primary industry segments, over the total number of alliance partners of the focal firm in the respective year.	SDC Platinum	Lavie, 2007
CEO experience	Age of the CEO.	Compustat	Herrmann & Datta, 2006
Size of total management team	The number of C-suite members for each firm.	Compustat	Karim et al., 2016
Firm size	The natural logarithm of total sales.	Compustat	Brower & Mahajan, 2013
Firm performance	Tobin's Q.	Compustat	Chen et al., 2016
R&D intensity	The ratio of R&D expenditure over annual sales.	Compustat	e.g., Long & Ravenscraft, 1993
Industry competitiveness	Herfindahl-Hirschman index.	Compustat	Hendricks & Singhal, 2005
Industry turbulence	An industry's sales and general administrative expenses over the industry's sales.	Compustat	Segarra & Callejón, 2002

our data was 149.62, with a standard deviation of 549.90.

Digital patent quality. As our second main dependent variable, we defined *digital patent quality* as a measure of the significance of a patent for future other innovations. Patent quality is an established measure that evaluates a patent's forward citations appearing in subsequent patents (Hall et al., 2005). This is particularly relevant to digital innovations because these are deliberately designed to be open and generative (e.g., Henfridsson & Bygstad, 2013; Jarvenpaa & Standaert, 2018; Yoo et al., 2010) and can spawn nearly unbounded wakes of innovation (e.g., Boland et al., 2007; Henfridsson et al., 2018; Kyriakou et al., 2022), making forward citations a useful measure.

We only measured forward citations that did not originate from the same patent holder (Hall et al., 2001). To correct for the age difference between patents, we first computed every patent's average forward citations within the same patent year. That is, a patent issued 10 years ago was compared to other patents with this characteristic to analyze whether the patent in question performed better, worse, or similar. Second, we corrected for biases arising from a firm's reputation and size that might affect absolute forward citations by forming a ratio of forward citations of digital patents to all of a firm's patents within a firm-year (Custódio et al., 2019; Hall et al., 2005). The average ratio of forward citations was 0.45, with a standard deviation of 0.43.

Independent Variables: Alliance portfolio characteristics

We constructed independent variables to capture four main characteristics of alliance portfolios: (1) portfolio size, that is, the number of alliance partners of a firm; (2) alliance portfolio degree of exploration; (3) alliance portfolio degree of internationality; and (4) alliance portfolio degree of competition. We retrieved the data from Refinitiv SDC Platinum's Mergers and Acquisitions database (SDC Platinum), which records publicly announced alliances.

Alliance portfolio size. We counted the number of newly entered alliances a focal firm engaged in during a particular year. The number of alliances in a portfolio is a frequently applied measure (e.g., Lahiri & Narayanan, 2013; Wassmer et al., 2017), as it draws a clear picture of the activeness of a firm concerning partnership building and broader exchange within selected alliance portfolios. Furthermore, since the termination of alliances is rarely disclosed publicly, and even then, reengagements are possible, alliance databases only contain information on new alliance announcements. In our data, the average number of alliances was 2.01, with a standard deviation of 2.6.

Alliance portfolio degree of exploration. For any given year, we divided the count of new partners (those with whom the firm has not previously been engaged) by the total number of all partners in the respective year (Lin et al., 2007). We examined the newness of an alliance partner by comparing each newly-listed partner of an organization with all previously known partners. If the partner had previously cooperated with the parent firm, we assigned a value of 0 for that year; if the alliance partner was new, we assigned a value of 1. As multiple partners joined forces in many alliances, we conducted this process individually for each partner. Because the exploration value for each firm's first firm-year in our sample was necessarily 1, we analyzed only the novelty of alliance partners from the second firm-year onwards. The resulting exploration index is a ratio between 0 and 1, with a higher score indicating a higher degree of explorative partnerships in the alliance portfolio. In our dataset, the mean of the sample's alliance portfolio's degree of exploration was 0.79, with a standard deviation of 0.32.

Alliance portfolio degree of internationality. We assessed the degree of a network's internationality by analyzing each alliance partner's domestic location. We constructed a binary variable to indicate whether the domestic location of a partner matched the parent firm's location (coded as 0) or whether the partner is foreign (coded as 1). Then, we calculated a ratio of foreign partners by the sum of all partners within a network for a given year (Lavie & Miller, 2008). A higher ratio indicates a greater degree of internationality in an alliance portfolio. We find an average degree of internationality of 0.50, with a standard deviation of 0.41.

Alliance portfolio degree of competition. We assessed the ratio of matches between a focal firm's primary industry segment (three-digit SIC) and its partners' primary industry segments, divided by the total number of alliance partners of the focal firm in the respective firm-year (Lavie, 2007). A higher ratio indicates that a firm relies on its network more in partnerships with same-industry partners in the current year. In our data, the average degree of competition was 0.24, with a standard deviation of 0.37.

Control variables

We added variables known to influence patent applications and alliance characteristics on the firm-level and the industry-level. All our control variables were computed based on data extracted from Compustat. Like all independent variables, control variables were lagged by one year, and winsorized at the 1 % level at both tails to adjust for outliers.

On the firm level, we controlled for a possible influence of the top management team on patents (Simsek et al., 2005). We measured *total management team (TMT) size* by counting the number of managers in the C-suite of every firm (Karim et al., 2016). Additionally, because a CEO decides on a firm's strategic direction (Garg & Eisenhardt, 2017), we also measured CEO age as a proxy for a *CEO's experience* (Herrmann & Datta, 2006). We then controlled for *firm size*, measured as the natural logarithm of total sales (Brower & Mahajan, 2013), because a firm's size has a significant impact on the capacity of an organization to engage in strategic activities; for example, they have access to lower cost of capital (Goerzen & Beamish, 2005). We also measured *firm performance*, operationalized as Tobin's Q, because it affects a firm's capacity and resources to engage and invest in new strategic activities (Chen et al., 2016). Finally, we measured *research and development (R&D) intensity* as the ratio of R&D expenditure over annual sales (e.g., Long & Ravenscraft, 1993), because of its association with alliance efforts and a firm's general interest in innovation (Duysters & Lokshin, 2011; Yamakawa et al., 2011).

On the industry level, we measured *industry competitiveness* and *industry turbulence* at sic codes level 2 to account for industry characteristics. We measured industry competitiveness via the Herfindahl-Hirschman index, which analyzes an industry's market shares (Hendricks & Singhal, 2005). We measured industry turbulence as an industry's sales and administrative expenditures divided by the industry's sales (Segarra & Callejón, 2002).

Model estimation strategy

Using hierarchical regression analysis, we proceeded in two stages. First, we examined our data for effects on the dependent variable *digital patent volume*, and second, on *digital patent quality*. Within each stage, we estimated a controls-only model (model 1), a set of four models to identify the individual effects of each alliance portfolio characteristic (models 2–5), and the effects of all alliance portfolio variables simultaneously (model 6).

We estimated negative binomial (NB) fixed-effects models for digital patent volume, due to the dependent variable's over-dispersion. We confirmed the use of NB over Poisson models by testing for a Poisson distribution in our panel data using Anderson-Darling distance (M(105209) = 149.6229, $p < 0.001$, R = 5000) and the energy goodness-of-fit test (E(215016) = 149.6229, $p < 0.001$, R = 5000).

To estimate digital patent quality, we used two-stage least squares (2SLS) models except for model 1 because 2SLS models account for endogeneity concerns for models that contain at least one alliance portfolio characteristic. We identified instrumental variables for each independent variable (Papies et al., 2017). Specifically, we used the industry's mean value that is widely used (e.g., Chung et al., 2019; Kleis et al., 2012) for each alliance portfolio configuration variable based on level 4 sic codes, as instrumental variables that are outside of our unit of analysis to meet exogeneity conditions (Ullah et al., 2021). The industry's mean is a suitable instrumental variable for two reasons (e.g., Germann et al., 2015): the focal firms face similar market conditions in comparison to their peers for operating in the same industry; and the focal firms and their peers face similar expectations because we sample our firms from the same stock performance index (S&P 500).

We estimated several statistics to assess the strength of our instruments. First, we estimated the correlations between each instrumental variable and the individual firm score. We found correlations of 0.72 for *alliance portfolio size*, 0.81 for *alliance portfolio degree of exploration*, 0.83 for *alliance portfolio degree of internationality*, and 0.83 for *alliance portfolio degree of competition*, confirming the strength of our instruments. Second, for each alliance portfolio configuration variable, we estimated the first stage of the 2SLS models, which show statistically significant effects for all our instruments (see Appendix A). Third, we assessed the strength of our instruments using the Cragg-Donald Wald F-statistic, which for all exceeded the 10 % Stock-Yogo critical value of 16.38. Fourth, we evaluated the presence of endogeneity using the Durbin-Wu-Hausman test for our two dependent variables. Both tests were statistically significant ($p < 0.001$).

We included year-fixed effects and industry-level controls (i.e., industry competitiveness and industry turbulence) to account for heteroscedasticity and systematic period effects (Lavie et al., 2010). We lagged all explanatory variables by one year. Finally, we reran all our models using a narrower operationalization of digital patents; specifically, we coded only patents that belonged to the CPC codes G06, G11, G16, and Y04 as "digital", yielding similar results.

Table 3 provides descriptive statistics and bivariate correlation coefficients. Bivariate correlation coefficients are below $|0.5|$ and

Table 3
Means, standard deviations, and correlations.

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1. Digital patent volume	149.62	546.90												
2. Digital patent quality	0.45	0.43	0.20**											
3. Alliance portfolio size	2.01	2.60	0.35**	0.08**										
4. Alliance portfolio degree of exploration	0.79	0.32	0.01	0.09**	0.01									
5. Alliance portfolio degree of internationality	0.50	0.41	0.04	−0.08**	−0.01	−0.00								
6. Alliance portfolio degree of competition	0.24	0.37	−0.06*	−0.11**	−0.02	−0.04	0.03							
7. CEO experience	51.42	16.14	−0.02	−0.02	0.06*	−0.03	−0.03	0.02						
8. Size of TMT	5.20	1.61	0.15**	−0.12**	0.05	0.01	0.05	0.09**	0.11**					
9. Firm size (log of sales)	9.36	0.94	0.16**	−0.04	0.19**	0.05	0.08**	−0.13**	−0.03	0.17**				
10. Firm performance	1.53	1.32	0.06*	−0.01	0.04	0.01	−0.03	0.14**	0.01	0.08**	−0.32**			
11. R&D intensity	0.07	0.10	0.11**	−0.03	0.08**	0.00	−0.04	0.32**	−0.01	0.05	−0.32**	0.45**		
12. Industry competitiveness	0.98	0.01	−0.05	0.17**	−0.14**	−0.02	−0.02	−0.07**	−0.03	−0.11**	0.01	−0.17**	−0.07*	
13. Industry market turbulence	0.16	0.05	0.26**	0.19**	0.08**	0.05	−0.05*	0.08**	−0.04	0.01	−0.42**	0.29**	0.33**	−0.16**

Note: N = 1387; M and SD are used to represent mean and standard deviation, respectively.
[*] indicates $p < 0.05$.
[**] indicates $p < 0.01$

none of the computed variance inflation factors (VIFs) exceeded 1.51 (M = 1.20). To explore potential multicollinearity concerns, we also estimated each independent variable in a separate model before estimating a comprehensive model (Lindner et al., 2020). We did not observe instable effects.

Findings

Digital patent volume

Table 4 presents the NB regression model results for digital patent volume. The controls-only model (Model 1) shows statistically significant effects for the variables firm size, firm performance, and R&D intensity, as well as our industry controls. Regarding alliance portfolio characteristics, we find statistically significant direct effects for alliance portfolio size (Model 2; $\beta = 0.16$, $p < 0.001$) and degree of competition (Model 5; $\beta = -0.60$, $p < 0.001$). These effects remain statistically significant in our full model (Model 6), where also degree of exploration ($\beta = 0.48$, $p = 0.001$) has a statistically significant effect.

Digital patent quality

Table 5 presents the regression model results for digital patent quality. The controls-only model (Model 1) shows statistically significant effects for the variables top management team size, firm size, R&D intensity, and our industry controls. The direct effects of each alliance portfolio characteristic show statistically significant effects, that is, for alliance portfolio size (Model 2; $\beta = 0.03$, $p < 0.001$), degree of exploration (Model 3; $\beta = 0.13$, $p = 0.002$), degree of internationality (Model 4; $\beta = -0.10$, $p = 0.002$), and degree of competition (Model 5; $\beta = -0.14$, $p < 0.001$). These effects remain statistically significant in our full model (Model 6).

Post-hoc analyses

We performed several tests to examine robustness, sensitivity, and boundary conditions for our findings. All specifications remained as in the main models unless noted otherwise.

First, we examined the robustness of our operationalization of digital innovation. We reran all statistical tests using a narrower

Table 4
Overview of models predicting digital patent volume.

	Model 1 (NB)	Model 2 (NB)	Model 3 (NB)	Model 4 (NB)	Model 5 (NB)	Model 6 (NB)
Alliance portfolio size		0.161 *0.020* *(<0.001)*				0.165 *0.020* *(<0.001)*
Alliance portfolio degree of exploration			0.256 *0.154 (0.096)*			0.479 *0.150 (0.001)*
Alliance portfolio degree of internationality				−0.009 *0.120 (0.939)*		0.008 *0.117 (0.944)*
Alliance portfolio degree of competition					−0.600 *0.139* *(<0.001)*	−0.559 *0.136* *(<0.001)*
CEO experience	0.004 *0.003 (0.141)*	0.003 *0.003 (0.365)*	0.004 *0.003 (0.157)*	0.004 *0.003 (0.141)*	0.004 *0.003 (0.229)*	0.002 *0.003 (0.603)*
Size of TMT	0.077 *0.031 (0.013)*	0.042 *0.031 (0.168)*	0.076 *0.031 (0.014)*	0.078 *0.031 (0.013)*	0.096 *0.031 (0.002)*	0.059 *0.030 (0.053)*
Firm Size (log of sales)	1.220 *0.062* *(<0.001)*	1.046 *0.063* *(<0.001)*	1.215 *0.062* *(<0.001)*	1.220 *0.062* *(<0.001)*	1.165 *0.062* *(<0.001)*	0.978 *0.063* *(<0.001)*
Firm Performance	0.144 *0.044* *(<0.001)*	0.170 *0.043* *(<0.001)*	0.138 *0.044 (0.002)*	0.144 *0.044* *(<0.001)*	0.128 *0.043 (0.003)*	0.145 *0.042* *(<0.001)*
R&D intensity	10.796 *0.579* *(<0.001)*	10.492 *0.569* *(<0.001)*	10.755 *0.579* *(<0.001)*	10.804 *0.580* *(<0.001)*	11.227 *0.601* *(<0.001)*	10.728 *0.591* *(<0.001)*
Industry competitiveness	26.651 *6.714* *(<0.001)*	41.535 *6.626* *(<0.001)*	26.127 *6.710* *(<0.001)*	26.614 *6.716* *(<0.001)*	28.313 *6.695* *(<0.001)*	42.144 *6.599* *(<0.001)*
Industry market turbulence	10.285 *1.025* *(<0.001)*	8.585 *1.016* *(<0.001)*	10.329 *1.027* *(<0.001)*	10.281 *1.026* *(<0.001)*	10.165 *1.022* *(<0.001)*	8.430 *1.013* *(<0.001)*
Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1387	1387	1387	1387	1387	1387
Nagelkerke's R^2	0.515	0.559	0.516	0.515	0.524	0.572

Note: For each variable in each model, the estimate is given in regular font, the standard error in italics, and the *p*-value are presented in parentheses.

Table 5
Overview of models predicting digital patent quality.

	Model 1 (OLS)	Model 2 (2SLS)	Model 3 (2SLS)	Model 4 (2SLS)	Model 5 (2SLS)	Model 6 (2SLS)
Alliance portfolio size		0.034 *0.006* *(<0.001)*				0.033 *0.006* *(<0.001)*
Alliance portfolio degree of exploration			0.129 *0.042 (0.002)*			0.127 *0.042 (0.003)*
Alliance portfolio degree of internationality				−0.102 *0.033 (0.002)*		−0.096 *0.033 (0.003)*
Alliance portfolio degree of competition					−0.136 *0.039* *(<0.001)*	−0.118 *0.039 (0.002)*
CEO experience	−0.00004 *0.0007 (0.959)*	−0.0004 *0.0007 (0.526)*	0.00003 *0.0007 (0.962)*	−0.0001 *0.0007 (0.858)*	−0.00002 *0.0007 (0.976)*	−0.0004 *0.0007 (0.538)*
Size of TMT	−0.026 *0.007* *(<0.001)*	−0.024 *0.007* *(<0.001)*	−0.026 *0.007* *(<0.001)*	−0.025 *0.007* *(<0.001)*	−0.024 *0.007* *(<0.001)*	−0.021 *0.007 (0.003)*
Firm Size (log of sales)	0.028 *0.014 (0.039)*	−0.0007 *0.015 (0.964)*	0.024 *0.014 (0.074)*	0.030 *0.014 (0.026)*	0.024 *0.014 (0.077)*	−0.005 *0.015 (0.749)*
Firm Performance	0.004 *0.010 (0.654)*	0.002 *0.010 (0.851)*	0.004 *0.010 (0.689)*	0.004 *0.010 (0.668)*	0.003 *0.010 (0.732)*	0.0004 *0.010 (0.968)*
R&D intensity	−0.339 *0.131 (0.010)*	−0.443 *0.133* *(<0.001)*	−0.337 *0.131 (0.010)*	−0.347 *0.131 (0.008)*	−0.171 *0.139 (0.219)*	−0.300 *0.141 (0.034)*
Industry competitiveness	10.307 *1.502* *(<0.001)*	11.638 *1.526* *(<0.001)*	10.381 *1.498* *(<0.001)*	10.214 *1.501* *(<0.001)*	9.953 *1.502* *(<0.001)*	11.261 *1.523* *(<0.001)*
Industry market turbulence	2.313 *0.231* *(<0.001)*	2.061 *0.237* *(<0.001)*	2.252 *0.232* *(<0.001)*	2.287 *0.231* *(<0.001)*	2.251 *0.232* *(<0.001)*	1.932 *0.237* *(<0.001)*
Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1387	1387	1387	1387	1387	1387
R^2	0.100	0.099	0.105	0.103	0.105	0.112
R^2 Adj.	0.094	0.092	0.098	0.096	0.098	0.103

Note: For each variable in each model, the estimate is given in regular font, the standard error in italics, and the *p*-value are presented in parentheses.

definition of digital patents to construct both dependent variables digital patent volume and quality. We reduced the list of considered CPC codes to a narrower set that only contained the codes G06 (Computing; Calculating; Counting), G11 (Information Storage), plus G16 and Y04 (both referring to Information and Communication Technologies) because these all explicitly refer to digital information and communication technologies. Appendix B summarizes the results for the estimation of model 6. The results are generally consistent with our main findings.[4]

Second, we examined the robustness of our estimations (see Appendix C for more details). For digital patent volume, specifically, we additionally estimated models using zero-inflated negative binomial (ZINB) analysis to account for excess zeros (Hilbe, 2011). ZINB analysis assumes that the excess of zeros is due to two distinct processes. On the one hand, an alliance may simply not engage in patent registrations at all. On the other hand, an alliance may not have registered any patents in a given year. Therefore, ZINB estimates one model that distinguishes alliances that register patents from those that do not and another model that estimates the effects of our independent variables on digital patent volume. In all our models, we included fixed effects (see Appendix C.1). For digital patent quality, we additionally estimated models using a control function to reduce concerns about endogeneity (Garen, 1984). Our estimations are summarized in Appendix C.2 and are generally consistent with our main results.

Third, we explored the sensitivity of our results regarding digital versus non-digital patents as innovation outcomes. We estimated two models (equivalent to model 6 in our main tests) for non-digital innovation patent volume (using negative binomial regression) and patent quality (using 2SLS). To operationalize non-digital patents, we subtracted the number of digital patents from the number of all identified patents for each firm-year observation. For non-digital patent volume, we found statistically significant effects for alliance portfolio size ($\beta = 0.10$, $p < 0.001$), degree of exploration ($\beta = -0.33$, $p = 0.031$), and degree of competition ($\beta = -0.32$, $p = 0.022$). Alliance portfolio degree of internationality ($\beta = 0.22$, $p = 0.075$) was not statistically significant. To operationalize non-digital patent quality, we subtracted the number of citations accrued for digital patents from the overall number of citations to patents for a firm in a given year to obtain a measure of the number of citations for non-digital patents. When estimating (the log of) the number of citations of non-digital patents, we found statistically significant effects for degree of internationality ($\beta = 0.42$, $p = 0.010$) but not for alliance portfolio size ($\beta = 0.06$, $p = 0.072$), degree of exploration ($\beta = -0.16$, $p = .452$), or degree of competition ($\beta = -0.33$, $p =$

[4] We also estimated 2-year and 3-year lagged effects and industry effects. Together, the results were generally consistent with our main findings and have been omitted for brevity.

0.086). We discuss the interpretation of these findings vis-à-vis our main findings below.

Finally, to understand boundary conditions, we analyzed the interactions of alliance portfolio characteristics with two key control variables: R&D intensity and industry competitiveness. Our reasoning is that R&D intensity is a key indicator of *internal resource availability* for innovation, while industry competitiveness is a key indicator of *external resource accessibility*. In addition to the variables' direct effects, we first estimated the effect of R&D intensity and industry competitiveness on each alliance portfolio characteristic's effect before estimating the interaction with all alliance portfolio characteristics. Appendix D summarizes and visualizes the estimated interactions for digital patent volume and digital patent quality.

Discussion

Summary and interpretation of findings

We examined how the configuration of alliance portfolios influences incumbent firms' ability to produce digital innovations, in terms of the volume and quality of digital patents. Generally, we find that alliances are positively associated with a firm's ability to produce digital innovations, both in terms of volume and quality. But we also note that the particular configuration of the alliance portfolio is an important strategic consideration, as the characteristics of the alliance portfolio are of different importance to digital vs non-digital innovation both in terms of volume and quality. We summarize the insights from our data analysis in Fig. 1, in which black outlines relate to aspects and relationships relating to digital innovations, grey outlines relate to non-digital innovations, and dashed lines indicate interaction effects of boundary conditions.

The framework in Fig. 1 underscores three main findings that connect to key properties of digital innovation and lead us to differentiate alliance portfolios for digital versus non-digital innovations. First, our main analyses demonstrate that portfolios of alliances that enable firms to produce more and higher-quality innovations differ along several of the four aspects (portfolio size, degree of exploration, degree of internationality, and degree of competition) we consider. While portfolio size matters regardless of whether firms create digital or non-digital innovations, a key difference lies in the degree of exploration, which increases digital patent volume but decreases non-digital patent volume. These results are consistent with and corroborate the proclaimed shift in organizing regime that is typically associated with digital innovation (Lyytinen, 2022; Nambisan et al., 2017; Yoo et al., 2012; Yoo et al., 2010) because they testify to the importance of distributed innovation processes (Nambisan et al., 2017; Yoo et al., 2012). For non-digital innovations, however, degree of exploration is negatively associated with patent volume, suggesting that trust and control play an important role in creating innovation, which is more difficult to establish with new partners (Gulati, 1995; Wassmer, 2010).

The inherently modular and open architecture of digital innovation along with the ability to represent an ever-growing share of economic offerings in digital form also facilitates the integration of heterogeneous resources, especially those that are outside a firm's usual network of competitors or complementors (e.g., Barrett et al., 2012). Our results show that alliance configurations with new partners are more likely to facilitate this integration (Yoo et al., 2012), rendering them more effective in the context of digital innovation.

The degree of internationality of an alliance portfolio is not at all (digital patent volume) or in fact negatively (for digital patent quality) associated with digital innovations, but positively associated with non-digital innovations (in terms of patent quality). Hence, for digital innovations, partners ideally come from similar cultural and geographic regions because international alliances induce costs that outweigh gains by overcoming cultural gaps, language barriers, and institutional or legal differences (Autio et al., 2021;

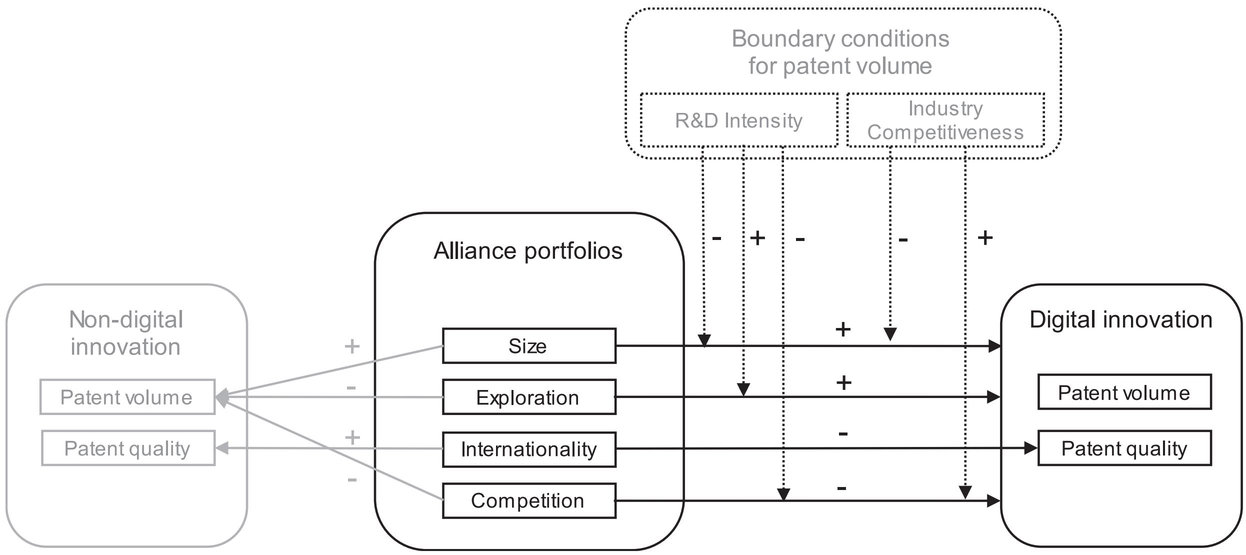

Fig. 1. Conceptual model of the relationship between alliance portfolios and digital innovations.

Nambisan, 2020). This is a crucial difference and novel addition to the literature (Inkpen, 1998; Zhang et al., 2010). Likewise, the degree of competition of an alliance portfolio appears to be a detriment to the creation of digital innovations but not necessarily to the creation of non-digital innovations.

Second, our findings also speak to the conditions in which alliance portfolios lead to more impactful digital innovations, which leads to an important distinction from non-digital innovations; an alliance portfolio's size and degree of exploration are beneficial for generating both more and higher-quality digital innovations, while the degree of competition is a detriment. Moreover, the degree of internationality matters to digital patent quality but not volume. This finding offers new insights into the relationship between digital innovation and international business (Autio et al., 2021; Nambisan, 2020). Here, the dominant narrative centers on the use of digital innovations to bridge geographical boundaries because of their semiotic nature, inherent modularity, and openness (Majchrzak & Malhotra, 2013; Zammuto et al., 2007). But in the creation of digital innovations, it would seem that location boundedness can be an advantage because it removes the coordination and translation costs that would be incurred in international alliance partnerships because of cultural differences, language barriers, local preferences, or digital sovereignty discrepancies (Lavie et al., 2010; Nambisan, 2020).

Third, while we found that our insights are generally robust, two main boundary conditions influence the strength of the identified relationships. In particular, the availability of internal and external resources for research and development activities influences the extent to which size and internationality of an alliance portfolio matter to digital innovation. The R&D intensity of firms strengthens the effect of internationality and weakens the effect of portfolio size. These results highlight the relevance of internal resource availability for innovation (Drees et al., 2013); internal resource availability can both support and hinder an organization's ability to create digital innovations (Kohli & Melville, 2019). For example, IT resources can amplify digital innovation because using IT can enhance a firm's ability to provide alliance contributions and coordinate dependencies. At the same time, IT resources can also conflict with digital innovation when they give rise to competing concerns and paradoxical tensions (Hund et al., 2021), such as when the digital codification of processes and workflows with IT becomes more rigid and thus acts an organizational barrier in the face of change.

Finally, external resource availability also affects alliance firms' ability to produce innovations (i.e., industry competitiveness) in a way that weakens the effect of alliance portfolio size and internationality. This is likely because the increased heterogeneity and dispersion of capabilities required for digital innovation in larger networks and of geographically dispersed partners increases the need for joint sensemaking (Nambisan et al., 2017). After all, digital innovation means that different partners must create a shared cognitive schema of both digital innovation products and processes (Lyytinen & Rose, 2003). Both the social and shared cognitive processes of (re-)framing and meaning-making (Wang et al., 2022) are time- and labor-intensive.

Theoretical implications

Our study makes several contributions to the literature on digital innovation and alliances. Our study shows that alliances—a well-understood organizational form—are also an effective vehicle for incumbent firms to engage in digital innovation. Yet, to the best of our knowledge, our study is the first to unpack the specific ways in which alliance portfolios influence the creation of digital innovations. Thereby, we contribute important insights about the conditions under which alliances enable incumbent firms to create digital innovation.

First, we show that engaging in alliances allows incumbent firms to create more and higher-quality digital innovations. This matters because digital innovations engender a new innovation regime and require distinct capabilities (Lyytinen, 2022). The ability to swiftly enter into new and adjacent markets by redeploying digital technology provides digital firms with a crucial competitive edge over incumbents (Huang et al., 2022). Competing with these emergent digital firms is notoriously challenging for incumbents (Chanias et al., 2019; Svahn et al., 2017). Our results indicate that alliances may improve incumbent firms' ability to create digital innovations to venture into strategically important fields and withstand competition with digital native firms that may possess more advanced digital resources. As our analysis shows, alliances can yield impactful digital innovations and therefore represent a way for incumbent firms to stay relevant.

Second, our results indicate that alliances are an effective way for firms to make up for a lack of digital capabilities. The speed at which digital native firms move and grow (Huang et al., 2022) is often problematic for incumbent firms; due to their scale, scope, and structures, they tend to move more slowly. However, our findings indicate that forming alliances may play an important role in responding to immediate competitive threats from new digital entrants (Hanelt et al., 2021). Past research suggests that responding to those threats is complex. It has also detailed numerous ways of staying alert in monitoring potential entrants, such as adding Chief Digital Officers to the management team (Tumbas et al., 2018), providing more risk-taking incentives to CEOs to increase their engagement in IT innovation (Choi et al., 2021), or facilitating continuous learning (Chanias et al., 2019). Our study adds to this literature by proposing the formation of alliances as an alternative response, specifically by partnering with other geographically close yet industry-distant and previously unknown partners.

A third contribution of our research is to the literature on alliances and innovation in general. The linkage between alliances and innovation has been explored in a variety of ways before, with a focus on organizational forms such as ambidexterity or joint venture creation (e.g., Connelly et al., 2019; Lin et al., 2007), or financial performance gains in terms of net income, return on investment, sales performance, or operating margins (e.g., Lahiri & Narayanan, 2013; Lavie & Miller, 2008; Nakos et al., 2014). Our study adds to this body of knowledge by providing a detailed examination of the importance of alliances to produce many and high-quality digital innovations logged as patents, and an examination of the key differences in alliance portfolio construction for digital vs non-digital innovations. Table 6 summarizes the insights we offer in this study and how they related to existing findings.

Managerial implications

Our study also contains insights that can be useful to directors and key executives striving to create more digital innovations in their organizations. The pressure on incumbent firms to innovate and adjust to an increasingly digital world is more critical than ever (Baskerville et al., 2020). According to a global survey (Capozzi et al., 2010), 84 % of executives agreed that innovation was the main driver for growth, yet only 6 % of them were satisfied with their firm's innovation performance.

Our study suggests that alliance partnerships, when properly configured, can be a key strategic vehicle for incumbent firms to create digital innovations. Partnerships can be attractive in terms of networking and leverage. However, they also bind resources and must be selected with care. We find that executives exploring the potential of alliance networks should regard the following considerations. First, size matters; for digital innovation, firms must assemble sufficiently large alliance portfolios to enable the recombination of different ideas, knowledge, resources, and capabilities. Second, firms should build alliances with new partners from distant industries instead of alliances with well-known allies and complementors. Third, location boundedness matters: even in digital innovation, local alliances help remove potential friction based on cultural, legislative, institutional, or language differences. Together, these strategic considerations will help firms not only produce more digital innovation patents but also raise their potential to influence further innovations by others.

Limitations and avenues for further research

Like any empirical study, ours has limitations. The patentability of innovations is a key boundary to our findings. Not all innovations meet the USPTO's patentability criteria (Hall et al., 2001), meaning that we will have missed several important digital innovations that were never logged as patents. However, this limitation affects all firms equally (Chung et al., 2019). Future research could compare our results to different data on digital innovation outcomes, such as new product announcements (e.g., Dos Santos et al., 1993; Teo et al., 2016).

Second, in our data construction, we only included patents eventually granted, resulting in some form of time truncation (Custódio et al., 2019). We thus limited our observations to 2006–2018 even though we collected patent data until 2022. This timeframe seemed reasonable to counteract the truncation bias (Hall et al., 2001) because 80 % of the patents by the firms in our study were granted

Table 6
Summary of contributions to the literature on alliances and innovation.

Portfolio characteristic	Key findings in the available literature	Our Findings
Alliance portfolio size	- Alliance portfolio size positively influences innovation (patent forward citations) and firm performance (net income) (Lahiri & Narayanan, 2013). - Alliance portfolio size explains performance differences among firms (Wassmer, 2010). - Alliance portfolio size does not significantly moderate the effect of ambidexterity in alliance portfolios on operating margins (Wassmer et al., 2017).	- Increasing alliance portfolio size enables incumbent firms to create higher volumes of digital innovations. - Digital patent quality significantly benefits from larger alliance portfolio size while non-digital patents do not. - These effects become more pronounced for firms with less R&D intensity and higher industry competitiveness.
Alliance portfolio degree of exploration	- The presence of dedicated institutional investors positively impacts the creation of exploratory joint ventures in alliances (Connelly et al., 2019). - A balance of exploration and exploitation across the function and structure domain of alliances leads to gains in profits and market value (Lavie et al., 2011). - Ambidextrous formations of alliance portfolios benefit large firms' asset turnover ratios but only in uncertain environments (Lin et al., 2007).	- A greater degree of exploration in alliance portfolios drives the creation of more and more high-quality digital innovations but not necessarily non-digital innovations. - Alliance degree of exploration shows a non-significant effect for non-digital innovation quality and a negative effect on volume.
Alliance portfolio degree of internationality	- Alliance complexity including international partners enhances the share of innovation sales (Duysters & Lokshin, 2011). - International alliances are a valuable source for learning and knowledge acquisition (Inkpen, 1998). - The relationship between alliance portfolio internationalization and return on investment is curvilinear (Lavie & Miller, 2008).	- A greater degree of alliance portfolio internationality negatively influences the volume (non-significant) and quality of digital innovation outcomes, while international portfolios boost the quality of non-digital patents. - The effect of internationality toward digital innovation (volume) benefits from R&D intensity and suffers from industry competitiveness
Alliance portfolio degree of competition	- The intensity of a firm's alliances with competitors has a curvilinear effect on return on equity (Luo et al., 2007). - Foreign alliances with competitors negatively influence international competitive sales performance (Nakos et al., 2014). - An increasing number of alliances with competitors negatively contributes to return on assets (Ritala et al., 2008).	- Alliance portfolios with partners from the same industry are associated with fewer digital innovations and non-digital innovations. - A greater degree of alliance portfolio competition is also negatively associated with the quality of respective digital innovations, however, there is no significant effect on non-digital innovation quality.

within four years.

Third, the process of examining alliances as antecedents of the incumbent's digital innovation is more complex than what we were able to capture. For example, as a measure of portfolio size, we rely on a count of newly-entered alliances because it is difficult to obtain accurate information on terminations as they are often not at all captured in alliance databases. Also, the data lacks specific details about partnering firms, such as organizational structure, human and social capital, and networking abilities. Each alliance portfolio is subject to more external and internal influences than accounted for in the study. To mitigate these limitations, interviews with top management teams responsible for the alliances could provide further insights (Choi et al., 2021; Li et al., 2021; Tumbas et al., 2018). Future research could analyze alliance portfolio configuration on a more granular level, such as assessing international partnerships on a country level or exploring corporate startup fit. The study also did not examine organization-internal factors like different organizational structures (Lyytinen et al., 2016) and the strength of network ties between partnering firms (e.g, Sammarra & Biggiero, 2008), which can impact digital innovation.

Finally, we caution the reader not to conflate our analysis with a causal examination of the relationship between alliance portfolio characteristics and digital patent volume and quality. Our data did not allow us to identify or examine underlying mechanisms in isolation. Future research could use qualitative field data collected from firms participating in alliance partnerships to better understand how participation in an alliance impacts the digital innovation process.

Conclusion

To compete in the digital age and successfully create new digital innovations, incumbent firms must update their existing capabilities with new capabilities and creating partnerships through alliances can enable this. We systematically estimated the relevance of four key strategic decisions in the formation of alliances: size, degree of exploration, internationality, and competition of a portfolio of partnerships. We show that the strategic decision to create joint digital innovations through alliances depends on the desired outcomes. Firms may desire to become more innovative (i.e., file more patents), or they may desire to create digital innovations that are more generative (i.e., file patents that can spawn subsequent innovations). Depending on this choice, they should configure their alliance portfolio differently. The nuanced insights we derived will allow firms to better understand the tradeoffs they need to make.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Appendix A: First stage models predicting each alliance portfolio configuration variables.

	Model 1 Alliance portfolio size	**Model 2** Alliance portfolio degree of exploration	**Model 3** Alliance portfolio degree of internationality	**Model 4** Alliance portfolio degree of competition
Industry Alliance portfolio size	0.987 *0.027 (<0.001)*			
Industry Alliance portfolio degree of exploration		1.000 *0.019 (<0.001)*		
Industry Alliance portfolio degree of internationality			1.000 *0.018 (<0.001)*	
Industry Alliance portfolio degree of competition				0.981 *0.019 (<0.001)*
CEO experience	0.003 *0.003 (0.278)*	0.000 *0.000 (0.703)*	−0.001 *0.000 (0.057)*	0.000 *0.000 (0.892)*
Size of TMT	0.075 *0.031 (0.014)*	−0.001 *0.003 (0.784)*	0.006 *0.004 (0.128)*	0.008 *0.004 (0.031)*
Firm Size (log of sales)	0.562 *0.059 (<0.001)*	0.006 *0.006 (0.332)*	0.001 *0.008 (0.947)*	−0.017 *0.007 (0.016)*
Firm Performance	0.031 *0.042 (0.461)*	0.006 *0.004 (0.157)*	−0.003 *0.005 (0.523)*	−0.004 *0.005 (0.437)*
R&D intensity	−0.237 *0.574 (0.680)*	−0.031 *0.060 (0.609)*	−0.108 *0.075 (0.148)*	0.127 *0.070 (0.068)*
Industry competitiveness	6.446 *6.607 (0.329)*	0.026 *0.689 (0.970)*	0.115 *0.853 (0.893)*	−0.038 *0.761 (0.960)*
Industry market turbulence	4.102 *1.004 (<0.001)*	0.048 *0.106 (0.650)*	0.059 *0.132 (0.652)*	−0.164 *0.117 (0.161)*

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	Model 1 Alliance portfolio size	**Model 2** Alliance portfolio degree of exploration	**Model 3** Alliance portfolio degree of internationality	**Model 4** Alliance portfolio degree of competition
Year Fixed effects	Yes	Yes	Yes	Yes
Number of Observations	1387	1387	1387	1387
Cragg-Donald Wald F-statistic	1383.302	2640.363	2935.448	2608.655
R^2	0.550	0.661	0.684	0.693
R^2 Adj.	0.546	0.658	0.681	0.691

Note: For each variable in each model, the estimate is given in regular font, the standard error in italics, and the *p*-value are presented in parentheses.

Appendix B

Appendix B: Statistical models (model 6 only) predicting digital patent volume, quality, and share using a narrow set of CPC codes as a definition of digital patents.

Model	**Model 6 (NB)** **Digital patent volume**	**Model 6 (2SLS)** **Digital patent quality**
Alliance portfolio size	0.167 *0.020 (<0.001)*	0.020 *0.006 (<0.001)*
Alliance portfolio degree of exploration	0.448 *0.153 (0.003)*	0.103 *0.038 (0.007)*
Alliance portfolio degree of internationality	0.105 *0.119 (0.380)*	−0.066 *0.029 (0.024)*
Alliance portfolio degree of competition	−0.433 *0.139 (0.002)*	−0.057 *0.035 (0.104)*
CEO experience	0.001 *0.003 (0.674)*	−0.0006 *0.0006 (0.308)*
Size of TMT	0.053 *0.031 (0.086)*	−0.020 *0.006 (0.002)*
Firm Size (log of sales)	0.933 *0.064 (<0.001)*	0.00004 *0.013 (0.998)*
Firm Performance	0.152 *0.043 (<0.001)*	0.003 *0.009 (0.769)*
R&D intensity	10.181 *0.600 (<0.001)*	−0.455 *0.126 (<0.001)*
Industry competitiveness	38.923 *6.725 (<0.001)*	6.110 *1.364 (<0.001)*
Industry market turbulence	8.965 *1.031 (<0.001)*	1.636 *0.212 (<0.001)*
Year Fixed effects	Yes	Yes
Number of Observations	1387	1387
R^2	0.571	0.082

Note: For each variable in each model, the estimate is given in regular font, the standard error in italics, and the *p*-value are presented in parentheses.

Appendix C

Appendix C.1: Overview of ZINB models predicting digital patent quality.

	Model 2 (ZINB)	**Model 3 (ZINB)**	**Model 4 (ZINB)**	**Model 5 (ZINB)**	**Model 6 (ZINB)**	**Model 6 (Logit)**
Alliance portfolio size	0.158 *0.021 (<0.001)*				0.161 *0.021 (<0.001)*	
Alliance portfolio degree of exploration		0.228 *0.166 (0.171)*			0.437 *0.155 (0.005)*	
Alliance portfolio degree of internationality			−0.057 *0.127 (0.655)*		−0.038 *0.118 (0.747)*	
Alliance portfolio degree of competition				−0.532 *0.147 (<0.001)*	−0.483 *0.140 (<0.001)*	
CEO experience	0.006 *0.003 (0.055)*	0.008 *0.003 (0.015)*	0.008 *0.003 (0.013)*	0.008 *0.003 (0.028)*	0.005 *0.003 (0.107)*	0.291 *0.111 (0.009)*

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(*continued*)

	Model 2 (ZINB)	**Model 3 (ZINB)**	**Model 4 (ZINB)**	**Model 5 (ZINB)**	**Model 6 (ZINB)**	**Model 6 (Logit)**
Size of TMT	0.060 *0.031 (0.053)*	0.094 *0.032 (0.003)*	0.097 *0.032 (0.002)*	0.110 *0.032 (<0.001)*	0.075 *0.031 (0.017)*	0.352 *0.266 (0.187)*
Firm Size (log of sales)	1.069 *0.058 (<0.001)*	1.237 *0.056 (<0.001)*	1.241 *0.056 (<0.001)*	1.194 *0.057 (<0.001)*	1.014 *0.060 (<0.001)*	−0.164 *0.465 (0.725)*
Firm Performance	0.197 *0.042 (<0.001)*	0.163 *0.041 (<0.001)*	0.169 *0.041 (<0.001)*	0.151 *0.041 (<0.001)*	0.172 *0.042 (<0.001)*	0.152 *0.396 (0.701)*
R&D intensity	12.503 *0.879 (<0.001)*	12.726 *0.891 (<0.001)*	12.820 *0.903 (<0.001)*	13.162 *0.923 (<0.001)*	12.786 *0.913 (<0.001)*	14.240 *3.874 (<0.001)*
Industry competitiveness	41.027 *5.596 (<0.001)*	25.430 *5.433 (<0.001)*	25.655 *5.443 (<0.001)*	27.666 *5.439 (<0.001)*	41.591 *5.611 (<0.001)*	−79.676 *39.268 (0.042)*
Industry market turbulence	7.485 *0.993 (<0.001)*	9.194 *0.954 (<0.001)*	9.119 *0.958 (<0.001)*	9.060 *0.967 (<0.001)*	7.345 *0.993 (<0.001)*	−8.000 *7.351 (0.276)*
Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1387	1387	1387	1387	1387	1387
AIC	12,720	12,795	12,796	12,784	12,709	12,709
BIC	12,723	12,797	12,799	12,786	12,712	12,934

Note: For each variable in each model, the estimate is given in regular font, the standard error in italics, and the *p*-value are presented in parentheses. AIC and BIC stand for Akaike and Bayesian information criterion respectively.

Appendix C.2: Overview of CF models predicting digital patent quality.

	Model 2 (Control Function)	**Model 3 (Control Function)**	**Model 4 (Control Function)**	**Model 5 (Control Function)**
Alliance portfolio size	0.051 *0.007 (<0.001)*			
Alliance portfolio degree of exploration		0.126 *0.045 (0.005)*		
Alliance portfolio degree of internationality			−0.103 *0.035 (0.003)*	
Alliance portfolio degree of competition				−0.341 *0.098 (<0.001)*
CEO experience	−0.0004 *0.0007 (0.524)*	0.0003 *0.0007 (0.693)*	0.0001 *0.0007 (0.885)*	0.0002 *0.002 (0.875)*
Size of TMT	−0.027 *0.007 (<0.001)*	−0.030 *0.007 (<0.001)*	−0.029 *0.007 (<0.001)*	−0.059 *0.016 (<0.001)*
Firm Size (log of sales)	−0.018 *0.016 (0.238)*	−0.026 *0.014 (0.060)*	−0.031 *0.014 (0.023)*	0.054 *0.029 (0.069)*
Firm Performance	0.004 *0.009 (0.657)*	0.007 *0.009 (0.481)*	0.007 *0.009 (0.452)*	0.012 *0.022 (0.567)*
R&D intensity	−0.535 *0.105 (<0.001)*	−0.396 *0.105 (<0.001)*	−0.406 *0.106 (<0.001)*	−0.576 *0.312 (0.065)*
Industry competitiveness	13.430 *1.539 (<0.001)*	11.690 *1.361 (<0.001)*	11.540 *1.362 (<0.001)*	34.590 *4.838 (<0.001)*
Industry market turbulence	1.772 *0.219 (<0.001)*	2.096 *0.202 (<0.001)*	2.135 *0.200 (<0.001)*	5.127 *0.464 (<0.001)*
Year Fixed effects	Yes	Yes	Yes	Yes
Number of Observations	1387	1387	1387	1387

Note: For each variable in each model, the estimate is given in regular font, the standard error in italics, and the *p*-value are presented in parentheses.

Appendix D

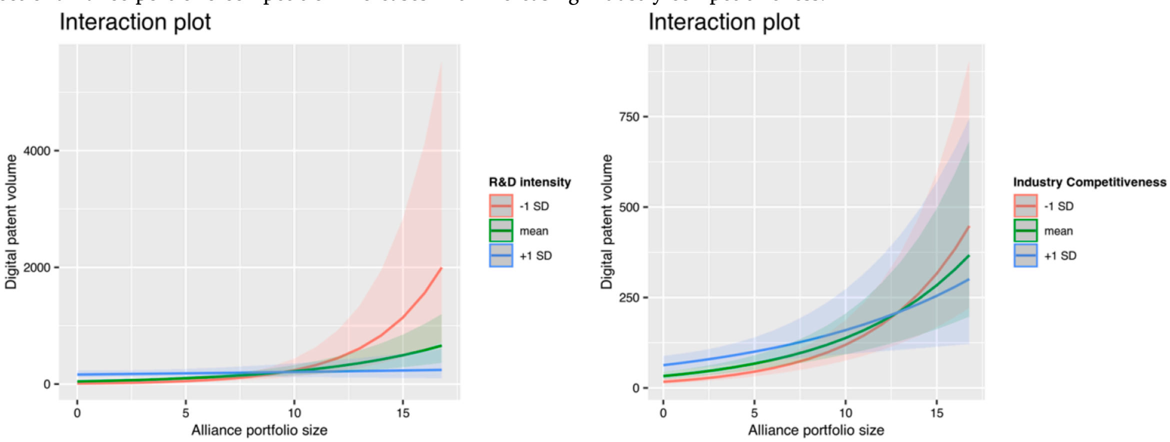
Appendix D.1 summarizes the interaction effects of alliance portfolio characteristics with R&D intensity and industry competitiveness for both dependent variables.

Appendix D.1: Overview of interaction effects.

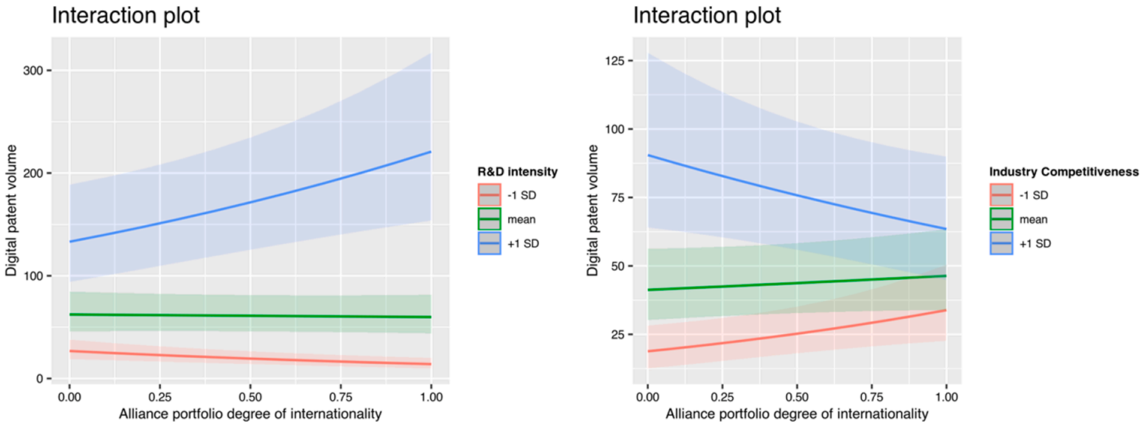
Dependent Variable	Digital patent volume Model 7 (NB)	Digital patent volume Model 8 (NB)	Digital patent quality Model 7 (2SLS)	Digital patent quality Model 8 (2SLS)
R&D intensity	11.997	10.500	10.309	0.458
	1.366 (<0.001)	*0.587 (<0.001)*	*12.487 (0.409)*	*1.040 (0.659)*
Industry competitiveness	43.034	47.250	3.457	12.989
	6.513 (<0.001)	*21.392 (0.027)*	*4.664 (0.459)*	*127.617 (0.919)*
Alliance portfolio size	0.268	5.122	0.010	–23.018
	0.027 (<0.001)	*1.774 (0.004)*	*0.047 (0.825)*	*18.160 (0.205)*
Alliance portfolio degree of exploration	0.452	−24.777	0.197	229.277
	0.167 (0.007)	*21.222 (0.243)*	*0.390 (0.614)*	*159.711 (0.151)*
Alliance portfolio degree of internationality	−0.464	46.278	−0.312	−134.678
	0.137 (<0.001)	*15.969 (0.004)*	*0.318 (0.326)*	*157.969 (0.394)*
Alliance portfolio degree of competition	0.358	−87.578	0.790	−282.026
	0.164 (0.029)	*19.585 (<0.001)*	*0.595 (0.184)*	*352.371 (0.424)*
Alliance portfolio size * R&D intensity	−1.525		0.050	
	0.266 (<0.001)		*0.829 (0.952)*	
Alliance portfolio degree of exploration * R&D intensity	2.456		−4.502	
	1.237 (0.047)		*12.242 (0.713)*	
Alliance portfolio degree of internationality * R&D intensity	6.065		3.150	
	1.243 (<0.001)		*7.984 (0.693)*	
Alliance portfolio degree of competition * R&D intensity	−10.035		−16.273	
	1.152 (<0.001)		*9.261 (0.079)*	
Alliance portfolio size * Industry competitiveness		−5.080		23.579
		1.815 (0.005)		*18.555 (0.204)*
Alliance portfolio degree of exploration * Industry competitiveness		25.674		–233.319
		21.604 (0.235)		*162.618 (0.152)*
Alliance portfolio degree of internationality * Industry competitiveness		−47.104		137.114
		16.256 (0.004)		*160.782 (0.394)*
Alliance portfolio degree of competition * Industry competitiveness		88.571		287.242
		19.948 (<0.001)		*359.006 (0.424)*
Controls Included	Yes	Yes	No	No
Year Fixed effects	Yes	Yes	Yes	Yes
Number of Observations	1387	1387	1387	1387
Nagelkerke's R^2	0.603	0.593		
R^2			0.012	0.004

Note: For each variable in each model, the estimate is given in regular font, the standard error in italics, and the *p*-value are presented in parentheses.

We find that R&D intensity moderates the relationship of alliance portfolio size on digital patent volume, whereas less R&D intensity is beneficial for larger alliance portfolio sizes (Appendix D.2). We also find moderating effects of R&D intensity and industry competitiveness toward the effects of alliance portfolio internationality and competition on digital patent volume (Appendix D.3). The effect of alliance portfolio internationality increases with increasing R&D intensity, while the effect of internationality decreases with increasing industry competitiveness. The effect of alliance portfolio competition decreases with increasing R&D intensity, whereas the effect of alliance portfolio competition increases with increasing industry competitiveness.



Appendix D.2: Moderating effects for the relationship between alliance portfolio size and digital patent volume with R&D intensity (left) and industry competitiveness (right).



Appendix D.3: Moderating effects for the relationship between alliance portfolio internationality and digital patent volume with R&D intensity (left) and industry competitiveness (right).

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