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IDENTIFYING START-UP PARTNERS: WHICH SEARCH PRACTICES AND COMBINATION STRATEGIES ARE EFFECTIVE?

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Start-ups are an important source of novel knowledge and product ideas for incumbents. We investigate which search strategies are positively related to the successful search for start-ups. We identify search instruments and their various uses: intensive or broad; stand-alone or combinatory. Finding 11 search practices in the literature, we evaluate how these practices were used by 97 respondents from a cross-industry and cross-national sample. Our results show that searching broadly and intensively is positively related to a successful search for start-ups and to firms' radical innovation capability. Specific tools that are positively related to search success are online contacts, desk research, external scouting partners, and start-up pitch events. Decision tree analysis provides effective combinations of search practices that innovation managers and purchasing managers can use. Employing these search practice combinations, we make incumbents aware of the routines used in distant knowledge search. These practices are dynamic capabilities that help them

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to remain successful in high-velocity markets. In identifying these search practices, we contribute to the literature on innovation routines and dynamic capability research.

Keywords: External knowledge sourcing; search strategies; start-ups; radical innovation capability; organisational search behaviour; organisational learning; search practice combinations; decision tree analysis; innovation procurement.

Introduction

Firms increasingly rely on external sources of knowledge and ideas (Criscuolo *et al*., 2018; van Wijk *et al*., 2008; Zhang and Cantwell, 2013). External knowledge is essential because it provides variations to problem solutions that were previously unknown to the firm. External knowledge also contributes to firms' combinatory search results (Fleming and Sorenson, 2001; Katila and Ahuja, 2002; March, 1991; Ehls *et al*., 2020). The literature on open innovation (OI) identifies various sources of external knowledge such as suppliers, universities, customers, and competitors (Van de Vrande 2013; West and Bogers, 2014: Brunswicker and Vanhaverbeke, 2015;). Recently, the role of start-ups as sources of new knowledge has received special attention (Homfeldt *et al*., 2019; Linton and Solomon, 2017; Weiblen and Chesbrough, 2015; Zaremba *et al*., 2017). By partnering with start-ups, firms aim to benefit from start-ups that are seen as flexible, alert, creative, and willing to take risks (Criscuolo *et al*., 2012; Lin and Li, 2013; Marion *et al*., 2012). In particular, firms hope to benefit from fast knowledge gains in distant and unfamiliar fields and to be better prepared for rapid change (Homfeldt *et al*., 2019; Lopez-Vega *et al*., 2016). For example, in 2020, Toyota invested $607 million in the start-up Pony.ai to keep abreast of developments in autonomous driving (Ludlow, 2020).

As sources of external knowledge, research has investigated how firms identify innovative suppliers (Pulles *et al*., 2014; Schiele, 2006). For example, firms were staging supplier competitions in the early stages of the innovation process (Langner and Seidel, 2009). Current studies have focused on identifying specific external knowledge partners and applying search approaches such as netnography for lead users (Belz and Baumbach, 2010) or patent analysis (Trautrims *et al*., 2017). Scholars have studied how firms identify start-ups but, so far, they have limited their research to the use of bridging structures, including sensing and scouting units (Gassmann and Gaso, 2004; Monteiro and Birkinshaw, 2017), liaison managers, and technology scouting groups (Spithoven *et al*., 2013).

Nevertheless, we do not yet understand the appropriate practices and search strategies that firms should apply to search for start-up partners. Because start-ups are usually unknown to the sourcing firm and no prior relationships exist, the search for such partners may be more challenging and require a more substantial effort than simply identifying established suppliers. Studies on the search for start-ups are either qualitative (Weiblen and Chesbrough, 2015) or restricted to a specific search practice; for example, self-organised pitch events (Homfeldt *et al*., 2017). However, we lack a quantitative study on how firms can best search for start-ups.

Here, search strategies refer to whether search practices are used independently or in combination (Laursen and Salter, 2006; Spithoven *et al*., 2013). Search combinations can include practices that firms use to a greater or lesser extent. Other search strategies involve using several practices regardless of usage intensity (search breadth) or only those with a high usage intensity (search depth) (Criscuolo *et al*., 2018). Hence, our first research question (RQ1) is: Which (combinations of) search practices lead to the successful identification of start-ups?

By accessing knowledge from start-ups, firms can increase their innovation performance (Wadhwa *et al*., 2016). Beyond recognising the benefits of collaboration with start-ups, our understanding is very limited on how firms implement a search for start-ups and what the corresponding practices entail. Organisational theory shows that firms generate new knowledge by combining external stimuli with internal routines (Zollo and Winter, 2002). Consequently, firms require continuous stimuli from their environment, which they can achieve by being open to external knowledge (Colombo *et al*., 2017). This study posits that the successful search for start-ups requires external impulses to generate radical innovations and expand capabilities. Consequently, a start-up can make a significant contribution to rejuvenating a firm. Accordingly, our second research question (RQ2) asks: What are the effects on the level of innovation in the sourcing firm (incremental vs. radical) of reliance on start-ups as innovation partners?

Based on a sample of 97 predominantly large firms from different industries, this paper sheds light on these research gaps by investigating how firms can successfully search for start-ups and what influence such searches exert on the searching firms' organisational capabilities. Thus, we add to the literature on external knowledge sourcing by focusing on start-ups as an increasingly important source of innovation. We also contribute by addressing the literature gap on the successful identification of partners beyond the existing supply base (Weiblen and Chesbrough, 2015; Zaremba *et al*., 2017). Furthermore, our findings contribute to the literature on organisational learning, innovation routines from the evolutionary perspective (Becker *et al*., 2005), and dynamic capabilities in the resource-based view framework (Kale and Singh, 2007). In detail, we explore whether search practices and their combinations support the identification of promising start-ups.

Finally, we identify the search strategies that are most effective for managers in various disciplines, such as R&D, corporate venturing, and procurement, and highlight the most beneficial practices.

Theoretical Background and Hypotheses

External knowledge sourcing as a critical open innovation practice

Following West *et al*. (2006, p. 286), OI is "a set of practices for profiting from innovation", combining internal and external activities as well as ideas and knowledge. The concept of practices was developed and used in organisational theory and sociology (Brown and Duguid, 2001). Practices are based on "(s)hared cognitive structures such as taken-for-granted scripts, schemas, rules, and norms" (Negro *et al*., 2010, p. 5) and are manifested in habituated behaviour and activities (Breunig *et al*., 2014). Brown and Duguid (2001, p. 204) stress that, for "workplace communication and coordination", it is vital "to share some practice", for example, concerning the production of new knowledge. The authors argue that conventional ways of searching for new knowledge have become obsolete, with knowledge now being sourced from both internal and external communities. They emphasise the "constant and pervasive need to dynamically balance and coordinate" both communities and to develop innovation practices (Brown and Duguid, 2001, p. 208).

OI practices focus on the external environment and are "people processes" (Ardito and Petruzzelli, 2017, p. 262) that involve the activities of various people (Breunig *et al*., 2014). Several authors relate OI practices to managers' decisions; for example, external cooperation or knowledge sources and subsequent activities or processes (Huizingh, 2011; Bellantuono *et al*., 2013). The search for external ideas and knowledge is an essential aspect of outside–in practices (Gassmann and Enkel, 2004). Huizingh (2011, p. 428) called attention to "external participation" in the form of "equity investments in new and established enterprises" as an endeavour that has potential merit in the search for start-ups. In general, the search for external knowledge and ideas has been defined by Ebersberger *et al*. (2013, p. 4) as "the systematic scanning of external environments". These environments include different actors (suppliers, customers, competitors, universities, conferences, trade associations) or public information sources (scientific publications, internet). They are a useful knowledge source to identify relevant external knowledge and potentially exciting start-ups (Ardito and Petruzzelli, 2017, p. 266). From a strategic point of view, the usage of search practices can differ in terms of the variety of practices used and the intensity of use, reflecting search breadth and depth (Laursen and Salter, 2006). Search practices and their combinations of similar or different usage intensity can become best practices and routines. If they form a stable pattern of one or several search activities, they can be considered a dynamic capability (Eisenhardt and Martin, 2000; Ebersberger *et al.*, 2013). We refer to them as search practice combinations in the sections that follow.

Theoretically, external knowledge sourcing is closely linked to the firm's knowledge-based view and organisational learning (Grant, 1996; March, 1991). Kogut and Zander (1992) state that innovation is related to a firm's capabilities to "exploit its knowledge and the unexplored potential of technology" (p. 391) and "generate new combinations of existing knowledge" (p. 392). Consequently, accessing external knowledge has long been seen as crucial to a firm's innovation success. Search practices relate to information concerning market needs and change as well as operational and technical knowledge (Laursen and Salter, 2006; Ebersberger *et al.*, 2013; Ardito and Petruzzelli, 2017). Specifically, external knowledge adds new variations of problem solutions that are unknown to the in-sourcing firm, thereby increasing the chances of finding novel linkages and developing innovative products (Katila and Ahuja, 2002). Extensive research provides evidence on the relationship between openness to external knowledge and a firm's innovation performance (Lakemond *et al.*, 2016; Leiponen and Helfat, 2010). Various external partners, including customers, suppliers, universities, and competitors, are essential sources of innovation (Rothaermel, 2002; West and Bogers, 2014).

External knowledge sourcing from start-ups

Start-ups have increasingly received attention as a promising external source of innovation (Homfeldt *et al.*, 2019; Weiblen and Chesbrough, 2015; Zaremba *et al.*, 2017) because they offer a unique set of capabilities that distinguish them from incumbent firms (Brunswicker and Hutschek, 2010; Gassmann *et al.*, 2010). Start-ups are also referred to as new ventures that have not been in existence for a long time (usually a maximum age of 8 years) (Song *et al.*, 2008). As start-ups lack resources, they may have to constrain their business development within a focused set of ideas (van Burg *et al.*, 2012). Thus, new product development may be more focused and dynamic in start-ups than in established firms (Rothaermel, 2002). Innovation is crucial for start-ups to quickly access market shares and early cash flows (Schoonhoven *et al.*, 1990). Because they are usually small, start-ups can sustain high flexibility and short command chains (Kickul *et al.*, 2011; Rothaermel, 2002). Hence, start-ups do not follow dedicated routines, which are often a barrier to innovation. Instead of being bound by already established structures, start-up processes are nascent and yield novel outcomes (Baker *et al.*, 2003; Katila and Shane, 2005). Finally, start-ups tend to possess a high-risk tolerance and open-mindedness, which helps to accomplish innovation, especially radical innovation (Audretsch *et al.*, 2018; Criscuolo *et al.*, 2012; Engel, 2011). Overall, this

Table 1. Search practices.

Search practices	Description	References
Desk research	Manual web-based search, automatic web screening, and external database services	Cruz-González *et al.* (2015) and Leiponen and Helfat (2010)
Scientific conferences/ publications	Visits to scientific conferences, reviewing publications	Cruz-González *et al.* (2015) and Leiponen and Helfat (2010)
Trade fairs/exhibitions	Visits to trade fairs and exhibitions	Cruz-González *et al.* (2015) and Leiponen and Helfat (2010)
Self-organised pitch events	Organising start-up events with open registration or professional search and pre-selection	Homfeldt *et al.* (2017, 2019) and Weiblen and Chesbrough (2015)
Fund of funds	Investment in VC funds managed by external VCs	Monteiro *et al.* (2017)
External scouting partner	Scouting by external service providers	Rohrbeck (2010)
Scouting satellite	Scouting department located in start-up "hot-spots"	Monteiro and Birkinshaw (2017)
Networking with business partners	Communication of potentially interesting start-ups by business partners can be suppliers, consulting firms, VCs	Monteiro *et al.* (2017)
Networking with universities/ research institutes	Potentially interesting spin-off firms are communicated by universities or research institutes	Cruz-González *et al.* (2015) and Leiponen and Helfat (2010)
Networking with non-partnering firms	Building a network with competitors, customers, and cross-industry parties	Cruz-González *et al.* (2015) and Leiponen and Helfat (2010)
Online contact opportunity for start-ups	Providing e-mail, landing, and webpages	Kohler (2016)

innovative potential of start-ups is a desirable feature and makes them interesting innovation partners for incumbents.

Search practices to identify start-ups

The literature lists many OI practices for knowledge search (Burcharth *et al.*, 2014; Chesbrough and Brunswicker, 2014; Mina *et al.*, 2014; van de Vrande, 2009). These OI practice lists are a starting point to identify start-ups employing search practices. Given the merits of start-ups' knowledge and ideas, the ways that established firms can identify start-ups in the early stages of the innovation process have garnered interest from the research community. The literature has revealed at least 11 different search practices (see Table 1).

The search for start-ups is located in the very early phase of alliance formation (Gulati, 1998; Kale and Singh, 2009). A first encounter between the sourcing firm and the start-up has not yet taken place. The firm's focus is on searching for and selecting suitable start-ups, often along defined search fields (Homfeldt *et al.*, 2019). The search includes an initial, financial, and technological evaluation and a rough selection based on a partnership's potential; for example, if there is a "match between a firm's existing competence and the availability of new opportunities" (Gulati, 1998, p. 294).

Start-ups can be identified through manual web-based search, the automatic screening of start-up databases, or visits to scientific conferences and public trade fairs (Cruz-González *et al.*, 2015; Leiponen and Helfat, 2010). Firms can also host pitch events during which start-ups present their ideas in front of experts (Homfeldt *et al.*, 2017; Weiblen and Chesbrough, 2015). Another approach is investing in funds that allow the firm that is willing to invest to participate in the deal flow of venture capitalists (VCs) (Monteiro *et al.*, 2017). Moreover, the identification of start-ups can be actively managed with the support of external scouting partners (Rohrbeck, 2010) or scouting satellites, which describe scouting departments located in start-up "hot-spots" (Monteiro and Birkinshaw, 2017). Apart from actively managed identification practices, the literature highlights networks of business partners (e.g., VCs or consulting firms), universities, and even non-partnering firms (e.g., competitors) as sources for identifying start-ups without actively searching (Cruz-González *et al.*, 2015; Cunningham and Menter, 2021; Leiponen and Helfat, 2010; Monteiro *et al.*, 2017). Finally, start-ups can directly contact the firm if the firm offers an open contact platform, such as a website or mailing address (Kohler, 2016).

We did not analyse the relation between single search practices and performance, even though this may be relevant for managers. First, evidence on the performance implications of single practices is too scarce to provide a foundation for hypotheses. Second, the performance impact of individual practices may be very context specific (for example, firm size, industry). Given these two reasons, we decided to analyse the search practice-performance relationship on the abstract level of combinations, search breadth, and search depth. Regarding combinations, Criscuolo *et al.* (2018) found that search strategies that combine internal and distant external knowledge lead to effective search routines. Accordingly, combinations of search practices for start-ups might result in greater search success and radical innovation capability. Combinations can also include search practices used less frequently.

Search strategies for the successful identification of start-ups

Research has focused on search breadth and search depth (Katila and Ahuja, 2002; Laursen and Salter, 2006). Laursen and Salter (2006, p. 131) introduced the concept of external search breadth and depth as "two components of the openness of individual firm's external search strategies". Search breadth has been defined as "the number of external search channels that firms rely upon in their innovative activity", whilst search depth is referred to as "the extent to which firms draw deeply from the different external sources or search channels" (Laursen and Salter, 2006, p. 134 following). Various OI studies use these constructs (Chen *et al*., 2016; Criscuolo *et al*., 2018; Laursen and Salter, 2006). Leiponen and Helfat (2010) indicate a positive relationship between search breadth and innovation success, which has been confirmed by Monteiro *et al*. (2017). Other studies show positive effects of search depth on incremental innovation (Chiang and Hung, 2010). Both search breadth and search depth have been associated with radical innovation and successful search for distant external knowledge (Chiang and Hung, 2010; Laursen and Salter, 2006).

Exploratory organisational learning is described as learning based on a broad and general search for knowledge and may lead to greater variation, flexibility, and innovation (Levinthal and March, 1993; March, 1991). Hence, expanding a firm's knowledge stock by accessing many search practices will allow a firm to search successfully. Different practices allow firms to target different segments of heterogenous start-up populations. Economic models have also shown the success of a parallel-path strategy, described as conducting multiple parallel searches (Baldwin and Clark, 2000; Nelson, 1961). These models illustrate that the "greater the number of draws from the distribution, the more likely it is that one of the draws will exceed the critical value needed" (Leiponen and Helfat, 2010, p. 225). Therefore, pursuing a larger number of start-up search practices increases the chance that one of these practices will lead to search success, defined as identifying sufficient, adequate, and value-generating start-ups.

However, the number of search practices a firm can successfully employ may be limited. One reason is that the concept of dynamic capabilities calls for stable patterns in different search strategies (Eisenhardt and Martin, 2000; Ebersberger *et al*., 2013). Lopez-Vega *et al*. (2016) introduced the concept of search paths characterised by different features. They argue specifically that, when direct feedback is desired in experiential search, firms develop "accumulated routines". The authors also point to bounded rationality, with firms not having the capacity to employ as many search practices as possible. Therefore, we expect that the search patterns that firms develop to search for start-ups will include only a few search practices. Hence, we hypothesise

Hypothesis 1 (H1): *For those practice combinations that are positively related to search success, the search practices are of limited search breadth.*

Concerning the depth of search practices, we follow the Laursen and Salter (2006) argument that the intensive use of search practices is essential to establish constant exchange and collaboration with external partners. Due to the high degree of discontinuity in the innovation processes, only specific sources and practices may be necessary to identify promising start-ups (Utterback and Abernathy, 1975). As proposed by the literature on social networks and social capital, strong and frequent contacts with specific knowledge sources support in-depth and fine-grained knowledge access and flow (Dyer and Nobeoka, 2000; Leana and Van Buren, 1999). Thus, a search relying intensively on selected search practices will lead to greater search success. We convert this line of reasoning on search practice combinations into the following hypothesis:

Hypothesis 2 (H2): *For those practice combinations that are positively related to search success, the search practices are of high search intensity.*

Organisational capabilities and the ability to generate radical innovations

Establishing and extending organisational capabilities is essential for firms to grow (Dosi *et al*., 2008; Penrose, 1959). According to Zander and Kogut (1995, p. 76), organisational capabilities are defined as the "organising principles by which individual and functional expertise are structured, coordinated, and communicated". The capability to innovate allows firms to accumulate, connect, and transform different knowledge types to generate new solutions (Lawson and Samson, 2001). Innovation capabilities concern competencies and expertise related to the creation of new products and their introduction (Hagedoorn and Duysters, 2002).

Whilst incremental innovation capabilities provide minimal differences to existing knowledge and routines, radical innovation capabilities expand existing knowledge to a significant extent. Radical innovation capabilities allow firms to create new-to-the-world products with high customer benefits and are, therefore, the source of competitive advantage (Chandy and Tellis, 1998, 2000). Subramaniam and Youndt (2005, p. 452) define a firm's radical innovation capability as "the capability to generate innovations that significantly transform existing products and services". Using radical innovation capabilities, firms fundamentally change the technological path and existing organisational capabilities by generating new knowledge that goes beyond existing skills (March, 1991).

In particular, established firms tend to under-invest in realising genuinely novel ideas because these mature firms face inertia relating to prior investments (Henderson, 1993). Previous experience and accumulated learning limit the success of established firms' distant search and the generation of radical innovations (Christensen, 1997) caused by existing routines (Levinthal and March, 1993), structures (O'Connor and Rice, 2013), and mental models (Tripsas and Gavetti, 2000). To overcome these restrictions and generate organisational knowledge, firms have to combine external stimuli with existing routines (Zollo and Winter, 2002). Thus, firms rely on continuous creative stimuli and are forced to develop openness capabilities (Colombo *et al.*, 2017; O'Connor and De Martino, 2006).

In particular, the search for start-ups opens up the search space to distant knowledge outside the firm's current knowledge base (Lopez-Vega *et al.*, 2016). The authors point to search fields — for example, different technologies — that must be determined in advance. Start-ups are potent engines of radical innovation because they are not limited by myopia and inertia (Levinthal and March, 1993). Start-ups possess characteristics that allow them to generate the necessary stimuli for radical innovations (Criscuolo *et al.*, 2012; Marion *et al.*, 2012). The knowledge of start-ups increases the innovation performance of in-sourcing firms (Dushnitsky and Lenox, 2006; Wadhwa *et al.*, 2016). Love *et al.* (2014) highlight the stimulation of learning processes when searching for partner firms and routines to interact with them. They also find evidence that management teams benefit from identifying, selecting, and interacting with external partners over time. Thus, a structured search for knowledge from start-ups may provide stimuli for identifying fundamentally new solutions. Taking these arguments based on organisational learning theory into account, we propose the following hypothesis:

Hypothesis 3 (H3): *Search success for promising start-ups is positively related to the firm's radical innovation capability.*

Method

Data collection and sample

To test our hypotheses, we surveyed a cross-industry sample using a self-administered internet-based survey. When collecting the data, we were faced with the challenge of investigating a topic that is in its infancy whilst, at the same time, addressing firms that were able to provide meaningful information. To achieve this, we collaborated with a large international venture capital and scouting firm that supported our survey's distribution amongst its business networks, consisting of firms that actively managed corporate-start-up relationships and searched for start-ups. Based on the key informant approach, managers responsible for identifying start-ups were contacted (John and Reve, 1982). In exchange for their participation, respondents were provided with a summary of the results. The sampling approach resulted in 97 usable responses containing complete information. To calculate the response rate, we used the 511 firms visiting the survey site as the population size, representing a response rate of 19.0% (Schweisfurth, 2017).

The response rate and sample size are comparable to prior studies on the topic of external knowledge search and radical innovation performance (Chang *et al.*, 2012; Martini *et al.*, 2017).

Our sample consists of firms from different industry sectors, such as automotive (26.6%), telecommunication (17.7%), services/finance (16.5%), manufacturing (15.2%), and healthcare (6.3%). More than half of the firms were located in Europe (56.5%), followed by Asia (28.9%) and (North-)America (14.5%). Furthermore, we selected primarily large multinational corporations, with about 40% of our sample firms having more than 5,000 employees. Annual revenues were above USD 500 million for more than half of the firms in our sample. Most of the respondents belonged to the management board or were top managers, as about 50% of the respondents were above senior management level, indicating a high level of informant quality (Montabon *et al.*, 2018).

Because late respondents are expected to be similar to non-respondents (Armstrong and Overton, 1977), we checked whether early (first 10%) and late (last 10%) respondents differed concerning our independent and dependent variables. As the *t*-test showed no significant difference ($p > 0.10$), we concluded that non-response bias does not pose a significant threat to the validity of our results.

Survey instrument and measures

The survey and its measures were developed through several stages representing the standard procedure (Dillman *et al.*, 2009; Sauermann and Roach, 2013). A preliminary questionnaire was drafted based on the reviewed literature and interviews with various practitioners, including two experts from a venture capital firm and two innovation managers from a large automotive manufacturer. We drew mostly on scales validated in prior studies that we adapted to our specific context. To assess face validity and content clarity, the survey instrument was discussed with 10 scholars and practitioners with expertise in innovation management, and their feedback was incorporated into the survey.

Dependent variables

Subramaniam and Youndt (2005) developed a measure for a firm's radical innovation capability, which is defined as the capability to generate innovations that significantly transform existing solutions. We used an extended four-item version of this construct employed by Menguc *et al.* (2014) (Cronbach's $\alpha = 0.78$, CR = 0.86, AVE = 0.61). The respondents were asked to rate the firm's capability for generating radical innovations relative to its main competitors by considering the extent to which the generated innovations in new products differ substantially from existing solutions and the degree to which customers' product experiences are significantly enhanced. Our measure for search success is adapted from Kock *et al*. (2015), who originally developed the scale to assess a firm's front-end success in identifying and generating promising ideas. We modified the items in order to fit the original scale to our specific context. Accordingly, the respondents were asked to assess the firm's success in identifying sufficient, adequate, and value-creating start-ups (five items, Cronbach's $\alpha = 0.80$, CR = 0.87, AVE = 0.56). All items were measured with a five-point Likert scale. The exact wording of the scales is presented in Appendix A. Search success serves as the independent variable in Hypothesis 3.

Independent variables and controls

Search breadth and search depth have been measured in the OI literature by adding responses on the usage and extent of various knowledge sources (Laursen and Salter, 2006, 2014; Leiponen and Helfat, 2010). We applied this algorithm in our measurement. Our survey listed 11 search practices, such as self-organised pitch events and networking with business partners. The search practices were deduced from the literature (see subsection "Search practices to identify start-ups") and approved for completeness and clarity by discussions with 13 experts from eight different firms, where the main business was the automotive industry. Amongst the experts were managing directors of corporate venture units and managers responsible for strategy, innovation management, and procurement. The search practices used in the survey are shown in Table 1.

Respondents were asked to indicate on a Likert-type scale how intensively they apply each of the search practices. A "0" indicated that the firm did not use the search practice, whilst a "5" indicated that it used it very intensively. Search breadth was measured as the sum of search practices used by the responding firms ranging from 0 to 11. First, each of the 11 search practices was coded as a binary variable, 0 being not applied and 1 being applied to any extent. Subsequently, the 11 search practices were added so that each firm received a value of 0 when none of the search practices was used, whilst the firm received the value 11 when all of the search practices were used. We applied a similar procedure for search depth but took account of how intensively the firm used a search practice. Specifically, a survey response of either 4 ("intensively used") or 5 ("very intensively used") received a binary value of 1; survey responses below (scores 0–3) received a binary value of 0. As in the case of search breadth, the final measure for search depth was obtained by adding these binary variables, the result of which is an index informing how many search practices a firm intensively searches for start-ups (see Cruz-González *et al.* (2015), Laursen and Salter (2006, 2014), and Leiponen and Helfat (2010) for similar measurement).

We used several control variables to preclude unobserved sources of variance in the hypothesis tests: for example, firm-specific details. Firm size is a commonly used control variable in innovation studies (Ahuja and Katila, 2001; Laursen and Salter, 2014). Larger firms have more resources, which may allow them to search more intensively for start-ups and establish more powerful R&D centres. To make the survey more simple to use, we allowed the respondents to select from five different options representing the firm's number of employees: 1 = "< 50", 2 = "51–100", 3 = "101–1,000", 4 = "1,001–5,000", 5 = "> 5,000" (Gao *et al.*, 2015). Second, we controlled the industry by using a set of five dummy variables. The industry dummy displays various environmental dimensions, including competition and technological opportunity (Veugelers, 1997). Third, we included region dummy variables because this might influence start-ups' search success and radical innovation capability (OECD, 2015).

Common method variance

As our data is self-reported, we acknowledge the potential threat of common method bias to the validity of our results. Following prior recommendations (Podsakoff *et al.*, 2003), we used various measures to counteract this potential problem in our data. We applied *ex-ante* remedies that concern the research design; for example, administering the questionnaire or the survey design and *ex-post* remedies after the responses were collected (Chang *et al.*, 2010). Concerning our research design, the survey provided only general information about the study's objectives but no information about the actual relationships under investigation. Specifically, our question design did not reveal which relationships are studied, as search breadth and search depth are measured as an additive index. Furthermore, we offered anonymity and confidentiality for respondents to reduce social desirability bias in the responses. In addition to the *ex-ante* remedies, we conducted a latent factor analysis equivalent to Harman's single-factor test (Harman, 1976). As the highest emerging factor was 19.8% and six components had eigenvalues greater than 1.0, no single factor constituted a large proportion of the total variance. In addition to Harman's single-factor approach, we applied the unmeasured latent methods factor test (Liang *et al.*, 2007; Perols *et al.*, 2013; Podsakoff *et al.*, 2003). As a first step, we generated a latent "common factor" covering all principal construct indicators. Then, we estimated the average substantive variance, described as the loading between the main construct and the indicator construct and the average method-based variance, which stands

Table 2. Results of latent factor loadings analysis.

	CL	CL^2	t_{CL}	MFL	MFL^2	t_{MLF}
SB	1.000	1.000	0.000	0.000	0.000	0.000
SD	1.000	1.000	0.000	0.000	0.000	0.000
SE1	0.552	0.305	3.855	0.210	0.044	1.405
SE2	1.019	1.038	7.517	–0.296	0.088	1.861
SE3	0.966	0.933	6.822	–0.184	0.034	1.398
SE4	0.562	0.316	3.263	0.204	0.042	1.274
SE5	0.646	0.417	3.446	0.075	0.006	0.383
RAD1	0.915	0.837	11.772	–0.117	0.014	1.230
RAD2	0.955	0.912	14.743	–0.147	0.022	1.643
RAD3	0.658	0.433	3.824	0.089	0.008	0.497
RAD4	0.551	0.304	3.638	0.215	0.046	1.648
Mean	0.802	0.681	5.353	0.004	0.027	1.031

Notes: $N = 97$.
SB = Search breadth; SD = Search depth; SE = Search success; RAD = Radical innovation capability; CL = Construct loading; MFL = Method factor loading. $t > 1.96$ = significant path at $p < 0.05$ (two-sided).

for loading the common factor on the indicator constructs. Whilst the substantive variance is on average 0.681, the average method-based variance is 0.027 (see Table 2). Hence, the ratio of substantive variance to method variance is approximately 25:1 and, thus, substantive variance is considerably greater than method variance. Furthermore, all of the method factor loadings are insignificant ($p > 0.05$). In sum, both tests indicate that common method variance should not be a problem in our study.

Analysis and Results

Descriptive data

Descriptive statistics and correlations for all variables are provided in Table 3 and the degree to which search methods are used is detailed in Table 4. The mean of search breadth represents how many search practices are in place at the investigated firms, whilst the mean of search depth shows the number of search practices with intensive use. With a maximum of 11 search practices, the mean of search breadth is very high overall (9.48), whilst the mean for search depth is only 3.57. This shows that firms apply many search practices but only a few intensively, with the highest values for networking with business

Table 3. Descriptions and correlations.

	Variable	Mean	SD	1	3	4	5	6
1	Firm size	3.52	1.56	1				
2	Search breadth	9.48	2.03	0.106	1			
3	Search depth	3.57	2.53	–0.062	0.408***	1		
4	Search success	3.23	0.79	–0.120	0.458***	0.437***	1	
5	Radical innovation capability	3.25	0.72	–0.267*	0.161	0.384***	0.371***	1

Notes: $N = 97$, except for firm size ($N = 82$). Industry and region dummies are excluded for the sake of clarity.
$^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 4. Method usage.

Search practices (multiple answers)	Usage intensity – mean (std.)*	Not used in %	At least low usage in %	At least medium usage in %	At least intensive usage in %
Desk research	3.16 (1.427)	7.2	76.3	45.4	17.5
Scientific conferences/publications	2.75 (1.429)	9.3	61.9	30.9	11.3
Trade fairs/exhibitions	2.90 (1.254)	5.2	69.1	32.0	8.2
Self-organised pitch events	2.47 (1.601)	15.5	53.6	30.9	10.3
Fund of funds	1.93 (1.685)	32.0	43.3	18.6	8.2
External scouting partner	2.08 (1.650)	25.8	43.3	22.7	8.2
Scouting satellite	2.63 (1.543)	15.2	61.9	32.0	9.3
Networking with business partners	3.21 (1.330)	7.2	76.3	45.4	15.5
Networking with universities/research institutes	3.09 (1.437)	8.1	75.3	46.4	13.4
Networking with non-partnering firms	2.86 (1.181)	2.1	66.0	30.9	6.2
Online contact opportunity for start-ups	2.13 (1.579)	23.7	45.4	21.6	6.2

Notes: * scale: 0 = "not used" to 5 = "very intensive".

partners (mean = 3.21), desk research (mean = 3.16), and networking with universities/research institutes (mean = 3.09). The use of external search agents, such as fund of funds and external scouting partners, is relatively low, which also applies to online contact opportunities for start-ups; for example, e-mail, landing, and webpages. Similar to prior studies (Cruz-González *et al.*, 2015; Laursen and Salter, 2006), we find a high correlation between search breadth and search depth, which supports our assumption that search breadth and depth are complementary.

For illustrative purposes, the usage frequency of the 11 search practices was related to the respective standardised regression coefficient of the search practice achieved in a simple ordinary least squares (OLSs) regression (see Fig. 1). With

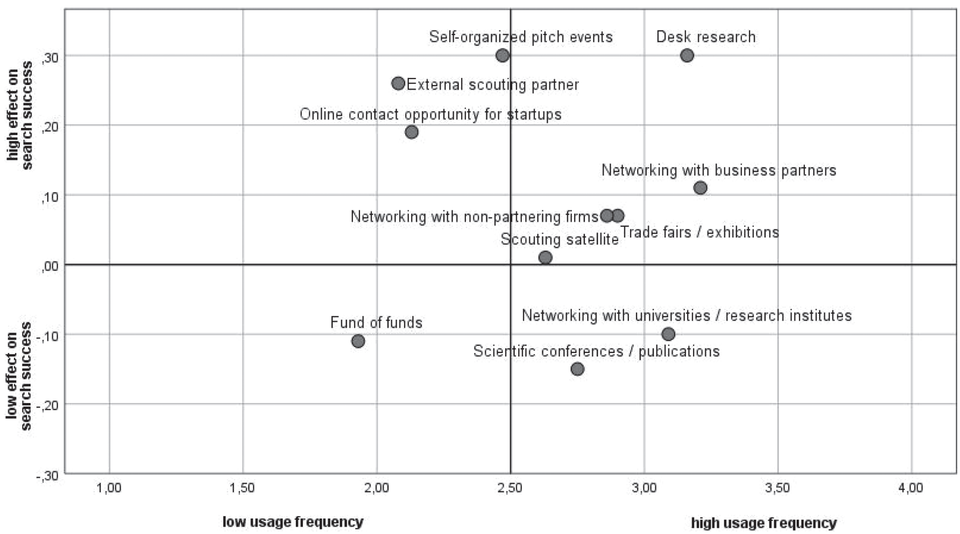
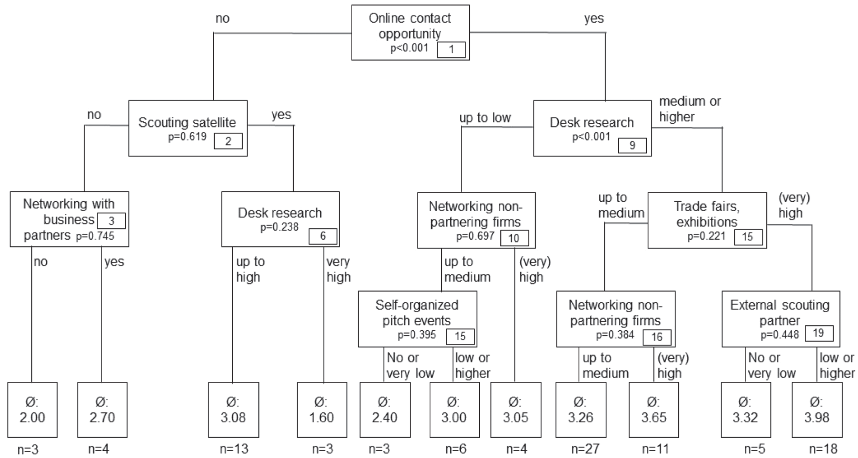


Fig. 1. Frequency of methods and search success.

search success as the dependent variable, the model has a good fit with an R^2 value of 0.446 (R^2 adjusted: 0.396) and an F value of 6.731 ($p = 0.000$). Self-organised pitch events ($\beta = 0.301$, $p = 0.003$), desk research ($\beta = 0.295$, $p = 0.003$), an external scouting partner ($\beta = 0.261$, $p = 0.014$), and online contact opportunity for start-ups ($\beta = 0.185$, $p = 0.053$) showed a significant, positive relationship with search success. In contrast, the university sector is of relatively low importance. The direct relationship with radical innovation capability is less distinct with an R^2 value of 0.191 (R^2 adjusted: 0.087) and an F value of 1.828 ($p = 0.061$). Only the relationship for networking with non-partnering firms was significant ($\beta = 0.233$, $p = 0.037$).

Hypotheses testing

To examine the effectiveness of different search practice combinations and to test Hypotheses 1 and 2, we used decision tree analysis. Decision trees are starting to be used in combination with machine learning techniques; for example, in predictive modelling and forecasting (Yagli *et al.*, 2019; Zhao *et al.*, 2021), and specifically in quality management (Kaparthi and Bumblauskas, 2020), hospitality management (Chattopadhyay and Mitra, 2019), and health research (Chern *et al.*, 2020). Decision trees are easy to apply, their results are easy to communicate, they are not sensitive to outliers, and they come with training data. Training data helps to identify structural relationships and later to verify model performance for new test data. However, compared to QCA/FsQCA, overfitting the training data is possible (Schneider and Grofman, 2006). The tree has to be pruned; for example, arguments



Ø: mean search success

Fig. 2. Decision tree of search practice usage.

have to be fixed, such as the maximum depth cut-off (maxdepth) (Bramer, 2016). The R package party kit based on tree-structured regression models (conditional inference trees) was used. Data were split into 70% training data and 30% test data. To better fit the solution with the data, we relied on correlation analysis. The best tree was identified with a correlation analysis with search success that resulted in 0.782 for the training data and 0.4395 for the test data. The arguments were set as follows: Mincriterion is 0.2, or the p value must be smaller than 0.8 for node splitting. Mytry allowed the testing of three search practices as node candidates. The depth of the tree (maxdepth) was best if set correspondingly to the mean value of search depth at 4. We found evidence in support of Hypothesis 1. Smaller or higher maxdepth values resulted in a worse fitting decision tree. In contrast, we could not find support for Hypothesis 2 since several combinations included one or more search practices on a low or medium intensity level (see Fig. 2).

To test Hypothesis 3, we conducted OLS regression ($n = 97$). However, for our firm size control variable, we had 15 missing values. To enhance the statistical power by including all available responses, we applied the mean imputation technique, which constructs a regression estimate for a missing data element based on all available data (Fichman and Cummings, 2003). For validation purposes, we also applied the listwise exclusion technique. The results remained constant. Collinearity statistics calculated for all regression analyses did not indicate problematic levels of multicollinearity. None of the variance inflation factors (VIFs; based on standardised variables) exceeded 2.0 and all were below the critical value of 10. Therefore, we conclude that multicollinearity did not strain our results

Table 5. Results of OLS regression analysis ($N = 97$).

	Dependent variable: Search success		Dependent variable: Radical innovation capability	
	Model 1 (Controls)	Model 2 (Effects)	Model 3 (Controls)	Model 4 (Effects)
(Constant)	2.818*** (0.283)	1.756*** (0.366)	3.373*** (0.256)	2.509*** (0.352)
Firm size	0.053 (0.065)	–0.039 (0.059)	–0.134 (0.059)	–0.152 (0.056)
Automotive	0.050 (0.244)	0.045 (0.214)	–0.062 (0.220)	–0.079 (0.209)
Manufacturing	–0.001 (0.260)	–0.094 (0.234)	0.207+ (0.235)	0.208* (0.222)
Healthcare	–0.035 (0.367)	–0.019 (0.323)	–0.057 (0.331)	–0.046 (0.313)
Telecommunication	0.226* (0.246)	0.161 (0.218)	0.226* (0.222)	0.150 (0.215)
Asia	0.358** (0.207)	0.155 (0.195)	0.063 (0.187)	–0.057 (0.185)
North America	0.059 (0.252)	0.010 (0.223)	–0.057 (0.228)	–0.076 (0.216)
South America	0.119 (0.786)	–0.019 (0.725)	0.142 (0.710)	0.102 (0.677)
Search breadth		0.292** (0.039)		
Search depth		0.317** (0.031)		
Search success				0.334** (0.091)
R^2	0.143	0.354	0.169	0.265
Adjusted R^2	0.065	0.279	0.094	0.189
F value	1.831+	4.708***	2.243*	3.491**

Notes: Coefficient estimates of OLS regression with standard errors (in parentheses) are shown. Reported estimates refer to standardised coefficients. The baseline category for the industry is "other." The baseline category for the region is "Europe."

$^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

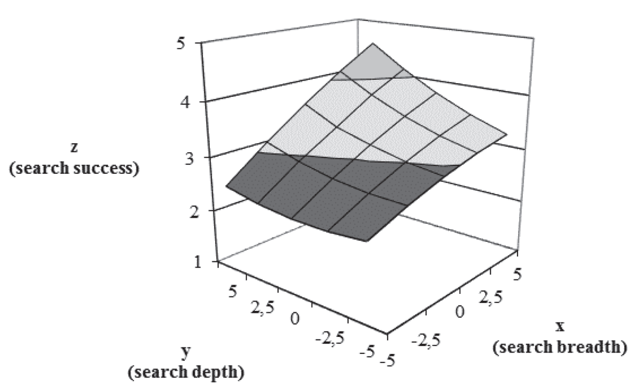
(Kutner *et al.*, 2004). No obvious outliers were detected, and residuals appeared to be normally distributed (Hair *et al.*, 2006).

The regression results are shown in Table 5. A small sample size only allowed us to analyse search breath and search depth, but not search practice combinations.

In Models 1 and 2, the dependent variable is search success whereas, in Models 3 and 4, radical innovation capability is the dependent variable (Hypothesis 3). Models 1 and 3 only contain the control variables. In Model 2, we add search breadth and search depth as the independent variables. Regression Model 4 adds search success as the independent variable. Models 2 and 4 show a good fit, as indicated by the high significance of the F values and the increase of R^2. Model 2 shows a positive and significant relationship for search breadth ($\beta = 0.292$, $p < 0.01$) and search depth ($\beta = 0.317$, $p < 0.01$) with the dependent variable search success. Thus, we can confirm previous research on search breadth and search depth. Moreover, in Model 4, search success is significant and positively associated with radical innovation capability ($\beta = 0.334$, $p < 0.01$), supporting Hypothesis 3.

With regard to the regression results, we performed several robustness checks. We applied percentile bootstrapping, which uses resamples to estimate the coefficients iteratively. We prevented our results from being dependent on existing outliers within our dataset (Efron and Tibshirani, 1994). The results using 5,000 resamples confirmed our findings. Similar results were obtained with different resample sizes (500, 1,000, 2,000, 3,000, and 4,000). We also confirmed our findings with the PLS algorithm that is recommended for small sample sizes of less than 250 observations (Reinartz *et al.*, 2009).

In line with previous studies on search breadth and depth (Katila and Ahuja, 2002; Laursen and Salter, 2006, 2014), we analysed our data for quadratic effects, using polynomial regression with surface analysis (Shanock *et al.*, 2010). Results did not show any curvilinear effects ($p > 0.10$, see Fig. 3). As only the search breadth and search depth slope show a significant relationship, we only support linear relationships.



$N = 97$.

Fig. 3. Polynomial regression graph.

Discussion and Implications

This paper provides the first empirical evidence for the positive effects of search strategies concerning identifying start-ups (RQ1) and their impact on radical innovation capability (RQ2). Our findings illustrate that broad and intensive searching allows firms to identify start-ups successfully and that these search strategies enhance firms' radical innovation capability. Moreover, several effective search practice combinations were identified. Below, we discuss our findings in relation to the literature on organisational learning, organisational capabilities, and external knowledge sourcing.

Research has highlighted the role of search breadth and search depth in organisational learning and has shown that routines develop over time. Learning routines concerning external partnering demonstrated the importance of prior relationships (Love *et al.*, 2014) or the combination of internal and external resources (Criscuolo *et al.*, 2018). One element in this learning process is identifying and selecting external partners that help improve innovation performance. Here, we have analysed the search for new partners — start-ups — in distant fields and identified their contribution to innovation performance and the development of routines consisting of several search activities. We contribute, as Love *et al.* (2014) pointed out, to an evolutionary perspective (Becker *et al.*, 2005) and to dynamic capabilities in the framework of the resource-based view (Kale and Singh, 2007).

Various studies show a curvilinear relationship between search strategies and innovation performance. This inverted U-shape is broadly explained as a result of "over-searching" since firms' absorptive capacity is limited and does not allow the transfer of infinite external knowledge (Cohen and Levinthal, 1990; Köhler *et al.*, 2012; Laursen and Salter, 2006). Various studies on external sources of knowledge and their impact on innovation performance confirm this reasoning (Rothaermel and Alexandre, 2009; Wadhwa *et al.*, 2016). Our study reflects a threshold for "over-searching" with the depth of the decision tree (4) and the mean value of search depth (3.57), pointing to the intensive usage of four methods. Similar to prior findings, our descriptive results show that search depth is much smaller than search breadth (Chen *et al.*, 2011; Chiang and Hung, 2010; Laursen and Salter, 2006). Interestingly, in the early era of OI, search depth was relatively small (0.96 with Laursen and Slater (2006) and 1.32 with Chiang *et al.* (2010)). The studies of Chen *et al.* (2011) with a search depth of 3.00 and Cruz-González *et al.* (2015) with 3.56 showed a similar high search depth. Overall, the ratio of search depth and breadth has increased with firms employing more methods intensively in parallel over time (Laursen and Salter, 2006: search breath 7.22, ratio 13.3; Chiang *et al.*, 2010: search breath 13.29, ratio 9.9; Cruz-González *et al.*, 2015: search breath 11.21, ratio: 26.8; our study: search breath 9.48, ratio 37.7). The search breadth and search depth of the applied search methods impact search success by approximately 30%.

Resource constraints may limit the ability of firms to use many search practices intensively. We observe that the firms in our sample use various search practices but tend to focus on specific ones in depth. The decision tree analysis reveals that a combination of four search practices seems sufficient to increase search success. Decision tree analysis allows the search methods to be broken down into effective combinations.

Consequently, the firms in our sample follow parallel search strategies combined with the frequent application of specific search practices. In line with previous research (Criscuolo *et al.*, 2018), potentially effective combinations consist of a mix of practices. IT-based practices that are developed, operated, and controlled by the firm are used together with practices attaining unfamiliar and distant knowledge; for example, an external scouting partner or networks with non-partnering firms. Usage intensity of the search practices in combination is mixed. Medium intensity is required for the combined search practices, but not the highest intensity.

The search for start-ups adds to the explorative phase of discovery (O'Connor and Ayers, 2005; O'Connor and De Martino, 2006). Our findings show that a successful search increases firms' radical innovation capability by 33.4% as start-ups provide robust and innovative ideas. Furthermore, the continuous screening and evaluation of radical ideas may enable the firm to follow a new explorative path and lead to greater variation and enhanced customer value (March, 1991).

Theoretical implications

Our findings add to the literature on external knowledge sourcing and OI by focusing on start-ups as a crucial external source of innovation (Weiblen and Chesbrough, 2015; Zaremba *et al*., 2017). We extend prior findings that were limited to searching for various external knowledge sources (Criscuolo *et al*., 2018; Ehls *et al*., 2020; Laursen and Salter, 2006) or other external partners, such as suppliers (Pulles *et al*., 2014; Schiele, 2006) or lead users (Bilgram *et al*., 2008). Our findings confirm that broad and intensive searching leads to higher search success. However, using specific combinations of search practices rather than a single practice is beneficial for increasing search success. The level of activities in these search patterns is of mixed but, at least, of medium intensity. Thus, we contribute to the research literature on dynamic capabilities (Eisenhardt and Martin, 2000; Ebersberger *et al*., 2013), different search paths (Lopez-Vega *et al*., 2016), and forward-looking searching (Ehls *et al*., 2020). We were able to transfer the frequently applied measurement for search strategies to a new context compared to prior analyses that focused on an internal search for knowledge or a search for external knowledge amongst many sources (Katila and Ahuja, 2002; Laursen and Salter, 2006).

We further show that distant knowledge provides additional new knowledge and explorative ideas to solve existing problems (Katila and Ahuja, 2002; March, 1991). The acquisition and application of external knowledge contribute to firms' renewal and an extension of their capabilities (Agarwal and Helfat, 2009; Eisenhardt and Martin, 2000). Knowledge from start-ups is one source of external stimuli that facilitates, in combination with existing knowledge, the generation of new knowledge (Fleming and Sorenson, 2001; Katila and Ahuja, 2002; Mawson and Brown, 2017). Contrary to prior research, which has only shown positive effects from collaborations on a firm's innovation performance (Laursen and Salter, 2006), we have analysed the outcome of search strategies on firms' capabilities. External creative stimuli are a prerequisite for generating radical innovations (Colombo *et al*., 2017; O'Connor and De Martino, 2006). Our findings indicate that discovering novel start-ups and assessing their ideas in the early stages of a firm's innovation process helps to ensure the continuation of such external stimuli. Overall, we show how a particular identification process for external partners can contribute to organisational learning and expand organisational capabilities.

We also demonstrate that firms start building their explorative learning capabilities because they are continually dealing with external radical innovations provided by start-ups. Thus, our study contributes to the ambidexterity literature by illustrating how firms can expand their explorative capabilities through continuous learning from external partners. As with prior research, our findings underline the benefits of exploration via externally oriented modes (Stettner and Lavie, 2014). In particular, firms enrich their knowledge bases by establishing ties with new partners with whom they have had no prior business relationships, such as start-ups (Lavie and Rosenkopf, 2006). Our results reveal that the search for start-ups provides the necessary impulse for firms to pursue explorative learning (Levinthal and March, 1993; March, 1991).

Finally, our findings add to the literature on the intersection of innovation management and purchasing (Jean *et al*., 2017; Kickul *et al*., 2011; Zaremba *et al*., 2017). We indicate how firms successfully search for innovative partners outside their established networks and extend the limitations of prior research, which has confined its consideration exclusively to the identification of established partners (Pulles *et al*., 2014; Schiele, 2006; Trautrims *et al*., 2017). This is particularly important because start-up identification is radically different. Start-ups are usually unknown partners without prior relationships to the sourcing firm and, therefore, a systematic search provides the source through which they can be identified. Hence, prior approaches to identifying established external partners are not sufficient and were extended in this paper by applying the concept of search breadth and depth to define successful search strategies for start-ups.

Managerial implications

Our findings allow managers to decide on which search practices are most effective. Regarding usage frequency, Fig. 1 shows that desk research is quite commonly used and valuable. In line with the decision tree results, firms should increase the usage frequency of self-organised pitch events, external scouting partners, and online contact opportunities for start-ups. Surprisingly, neither networking with universities nor visiting scientific conferences significantly affects search success. This result is in line with Ehls *et al.* (2020, p. 421), who "expect a shift towards more unfamiliar solvers and multiple external sources".

Regarding our second dependent variable, radical innovation capability, only the search practice networks with non-partners are significantly related. Thus, we conclude that networks with businesses are most important, and self-organised start-up events provide the highest direct search output. Overall, managers should invest in combinations of multiple search practices — in particular IT-based ones, which are very effective but do not involve high costs — and combine them with meeting platforms (trade fairs, pitches), networks with non-partners, and external scouting partners.

Limitations and future research

This study has several limitations that can be addressed by further research. First, our dataset is relatively small. Considering that start-up search is a relatively novel practice, it was a challenge to identify managers that systematically search for start-ups. Second, this study includes subjective measures. Although we cannot exclude the presence of common method variance, the design of the hypotheses, the application of ex-ante remedies, and the statistical tests applied suggest that common method variance is not a cause for concern in our study. Third, our analyses are cross-sectional. Thus, our data renders it impossible to test for causal effects over time; for example, concerning the effect of successful search on the radical innovation capability of firms.

Nevertheless, we can point to some encouraging indications for the model and its dependencies. Longitudinal studies may help to test and substantiate some of our cross-sectional findings. We recommend using objective data for future studies and incorporating additional variables into future research — for instance, those focusing on specific relationships between incumbent firms and start-ups. Fourth, we did not consider how successful searches result in radical product innovations. Our findings show that the knowledge acquired from searching for start-ups increases firms' radical innovation capabilities. Nevertheless, we do not know the micro-processes behind the relationships of a successful search for start-ups, radical innovation capability, and the actual generation of radically innovative products. Future studies could analyse these processes by applying qualitative designs.

Furthermore, whilst we focused on the identification phase, future research could extend the focus to the post-identification stage; for example, by investigating practices that include evaluation of the potential of identified start-ups before entering into collaborations. A classification of the search practices according to the location of the achieved ideas and information in the knowledge space — for example, familiar or distant knowledge — would be an interesting pursuit. The development of routines and synergy effects in combinations of search practices should be investigated. Researchers could use a qualitative approach to obtain an in-depth picture of how a search practice combination evolves and how usage intensity is reflected in the activities' design. Finally, an exciting path for future research is investigating "dynamic managerial capabilities" (Helfat and Martin, 2015) concerning corporate-start-up relationships. Such studies could focus on the impact of searching for start-ups on an individual manager's cognitive learning. Going beyond search processes, the development of routines to interact with start-ups and to manage ensuing partnerships should be investigated (Love *et al.*, 2014). Overall, we hope that our research will encourage scholars to examine start-ups as an external stimulus for organisational learning.

Appendix A. Multi-Item Scales

Scales		Factor loadings
Search success ($\alpha = 0.80$; CR = 0.87; AVE = 0.56)		
Please indicate your opinion on the following statements referring to your firm's search success regarding the identification of start-ups (1 = strongly disagree; 5 = strongly agree)		
SE1:	We identify many start-ups for our portfolio.	0.730
SE2:	We identify sufficiently "good" and/or "right" start-ups for our portfolio.	0.761
SE3:	Our current start-up portfolio will strengthen our competitive positioning.	0.808
SE4:	With our current start-up portfolio, we will be able to strongly increase our sales of new products within the next three years.	0.740
SE5:	Overall, our current start-up portfolio has a strong value-generating potential.	0.714
Radical innovation capability ($\alpha = 0.78$; CR = 0.86; AVE = 0.61)		
How would you rate your company's capability to generate the following types of innovations in the products? (1 = much weaker than competition; 5 = much stronger than competition)		
RAD1:	Innovations that make existing products obsolete.	0.834
RAD2:	Innovations that fundamentally change existing products.	0.853
RAD3:	Innovations that significantly enhance customers' product experiences.	0.718
RAD4:	Innovations that require different ways of learning from customers.	0.701

Notes: α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

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