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Distant or Local? The Roles of Knowledge Search on General Purpose Technology Innovation in Emerging Industries

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ABSTRACT

Due to the inherent complex tensions in General Purpose Technology (GPT) in emerging industries, namely those between "generality" and "emergance," firms in emerging industries often face the dilemma of choosing distant search or local search in GPT innovation. The core research question of this paper is: How do the different knowledge search strategies affect GPT innovation in emerging industries? And do industry alliances play a moderating role between them? Based on a knowledge-based view, this paper takes 380 firms in emerging industries as total samples and 196 firms in emerging industries as subsamples to examine the impact of distant, local, and balanced knowledge search on the GPT innovation in emerging industries, finding: (1) Different knowledge search strategies have differential effects on the GPT innovation in emerging industries. (2) The heterogeneity of industry alliances positively moderates the relationship between distant search, balanced search, and GPT innovation in emerging industries, and weakens the relationship between local search and GPT innovation in emerging industries. This paper clarifies the relationship between knowledge search strategies and GPT innovation in emerging industries, and also provides management inspiration for the emergence and improvement of GPT innovation.

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Introduction

General purpose technology (GPT) in emerging industries, characterized by general applicability (Rosenberg & Trajtenberg, 2004) and strong complementarities with existing or potential new technologies (Bresnahan, 2010;Coccia, 2018), allows the application of emerging technologies to the technical and knowledge fields of diverse industries (Gambardella & Giarratana, 2013; Appio et al., 2017), resulting in a whole that is greater than (or, at least, different from) the sum of its parts (Alexander et al., 2012) and affecting the whole economy (Jovanovic & Rousseau, 2005). GPT is known as platform technology paving the way for the continuous innovation of a large number of complementary technologies in the future (Feldman & Yoon, 2012; Coccia, 2017), and in this regard, GPT is also known as disruptive technology (Coccia, 2020). Though the productivity gains from GPT have varied across economies and industries (Hall, 2014), the platform effect of GPT in emerging industries makes it a driver of the development of industries and states, which can promote overall technological progress and economic development (Devezasa et al., 2005; Strohmaier & Rainer, 2016). Many governments have devoted tremendous effort to support the breakthrough and spillover of GPT. For example, the European Union's science and technology framework plan, the United States' Technology Innovation Program (TIP), and China's "Guidelines for the Development of Key Industrial Common Technologies (2011)" all reveal great support for GPT innovation in industrial technologies.

There exist inherent complex tensions between "generality" and "emergence" in GPT innovation in emerging industries, raising special requirements on the knowledge search strategies of firms in emerging industries, that have received little scholarly attention. On the one hand, "generality" demonstrates the characteristics of fundamentality, penetration, and reproductivity of GPT (Bresnahan & Trajtenberg, 1995; Coccia, 2017), requiring firms to repeat numerous local searches and carry out in-depth utilization in existing technology fields (Aharonson & Schilling, 2016). On the other hand, "emerging" characteristics include the leading edge nature, prospectiveness, and transcendence of GPT (Rotolo et al., 2015), which require firms to conduct a large number of distant searches across existing knowledge boundaries (Aharonson & Schilling, 2016). Furthermore, the requirements for distant search have become more prominent, especially in the context of rapid iteration and replacement of emerging technologies. Thus, how do the knowledge search strategies of firms

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affect the innovation of GPT in emerging industries? This is the core research question of this paper.

GPT has been widely discussed in the literature. After the pioneering paper on "general technology" research by Bresnahan and Trajtenberg (1995), this concept has been expanded to various other areas, such as economic history (e.g., Crafts, 2004), industrial organization (e.g., Lindmark, 2005), economic policy (e.g., Zon & Kronenberg, 2007), and innovation research (Andergassen et al., 2017). In the field of management, existing research on GPT has focused on measurement and identification methods (Leydesdorff, 2008; Huang & Zhang, 2014; Luan, 2015), the role of government procurement (Coccia, 2015; Raiteri, 2018), patent licensing (Gambardella & Giarratana, 2013), market structure (Gambardella & Giarratana, 2013), the role of research institutions (Barirani et al., 2017), industry-university research (Fan et al., 2018), and technology diffusion (Goldfarb, 2005). In the Industry 4.0 era, scholars have paid more attention to GPT with strong technological spillover effects (Venturini, 2022), and have argued that differentiated knowledge search strategies or R&D moods will have an important impact on this kind of unique technological innovation (Strazzullo et al., 2022; Yang et al., 2022).

Moreover, due to the multiple requirements of knowledge in the GPT innovation in emerging industries, the role of industrial technology innovation alliances (hereinafter, "industry alliances") has drawn much attention. Industry alliances can connect various innovation subjects in the market, such as industry, university, research institute, and upstream/downstream firms, while alliance members can obtain complementary resources and capabilities beyond the organizational boundary. This thus raises the question of how industry alliances play a contingent role in the relationship between knowledge search strategies and GPT innovation in emerging industries. This constitutes the other research question of this paper.

Based on the data of 38,244 patents of China's strategic emerging industries, taking 380 firms in emerging industries as the total sample and 196 firms in emerging industries with alliance information as the sub-sample, this paper explores the impact of distant/local search strategies on GPT innovation in emerging industries, as well as the moderating role of industry alliance heterogeneity.

Theoretical basis and research hypotheses

In the era of the knowledge economy, knowledge has become a strategic resource for so many firms that it is a significant restriction for a firm to rely solely on itself to obtain knowledge. Searching for knowledge from outside has become an important action of firm innovation (Yang et al., 2022). As a special kind of technical knowledge, general purpose technology (GPT) has the characteristics of "emerging" and "platform" technology. GPTs are not only pervasive in their use and disruptive in their effects but also stimulate technical improvements and innovational complementarities far from their sector of origin (Venturini, 2022), especially in emerging industries (Haupt et al., 2007). To achieve GPT innovation, firms in emerging industries should choose different search strategies suited to match external knowledge. At the same time, as a knowledge-gathering place, an industry alliance has tight heterogeneous information flow and technical resources, which also affect the knowledge acquisition of firms.

Distant vs local search and innovation of GPT in firms in emerging industries

The concept of innovation was first proposed by Schumpeter (1982), who regarded the innovation process as the flow and realization of innovation elements to meet the innovation goal. The innovation process is affected by a variety of sources of information: firm-internal sources, external market sources, and educational and research institutions; and may be hampered by economic factors (OECD, 2005). Innovation is crucial to the survival of companies, especially in a highly competitive market (Freitas et al., 2021).

General purpose technology (GPT) is a technological solution that can be applied to different markets (Ardito, et al., 2016) that has formed the basis of complementary innovation waves in a variety of industries (; Bauer and Knieps, 2018; Yang et al., 2022), hence maintaining and strengthening economic growth. GPT innovations are predominantly generated in firms from various industries (Castellacci, 2008) and have a great deal of scope for ultimate implementation, playing a "bridging" role in the fusion between sectorally separate technologies (Qiu and Cantwell, 2018).

Based on previous views, we define GPT innovation as the entire process of business optimization aimed at achieving specific economic goals and efficient application of common industrial technologies that generate new common technologies through application research and optimization of technology combination from new ideas of technology and finally yields social and economic benefits through practical application.

GPT constitutes the technological cornerstones of a wide range of industries, with the vital characteristics of fundamentality, penetration, platform-base, and reproductivity (Bresnahan & Trajtenberg, 1995; Coccia, 2017). The evolution of any technology in the long-run is not independent (Coccia & Watts, 2020), and requires a certain knowledge base (Ardito et al., 2016). However, considering the natural technological distance and segments between different industries, firms should meet the special requirements on knowledge search distance while developing GPT.

Building on concepts introduced by March and Simon (1958) and Nelson and Winter (1982), local search has been defined as the behavior of any firm or entity searching for solutions in the neighborhood of its current expertise or knowledge (Stuart & Podolny, 1996); distant research defines exploitation activities as those in which the firm leverages its existing knowledge base, while exploration involves the search for new knowledge in domains that are relatively distant from the firm's core base of knowledge (Mudambi & Swift, 2014).

The distant search aids firms in entering new technology fields, gaining knowledge of fields with which they are not conversant, and avoiding similarity traps (Ahuja & Lampert, 2001), thereby contributing to the technical foundation for the innovation of GPT. Moreover, a distant search by firms in emerging industries helps them span the inherent knowledge boundary and conduct a cross-border search, which ensures uniqueness and promotes the generality and penetration of emerging technologies. Finally, knowledge derived from an extensive search is more likely to be understood and admitted as the "common view" by various industries, enabling its application in different sectors (Banerjee & Cole, 2010). Numerous studies have argued that general technology results from basic and high-risk exploratory research (Trajtenberg et al., 1997; Adner & Levinthal, 2002; Fleming, 2001; Rosenkopf & Nerkar, 2001; Coccia, 2017;). Especially in the field of emerging technologies, due to their novelty, unpredictability, and ambiguity (Rotolo et al., 2015), distant searches across borders seem particularly important. Based on a study of the optical disc industry, Rosenkopf and Nerkar (2001) stated that general technologies come from the exploration and reorganization of knowledge across technologies.

However, the positive effects of distant search on the convergence, cross-borderness, and novelty of emerging technologies also show certain boundary conditions. First, GPT requires firms to develop mainstream, general, and basic technologies in specific technology fields; thus, when the search distance of firms in emerging industries is too great, it is easy to deviate from the requirements of existing technology on "general technology" and become a "niche" technology contrary to the requirements of the nature of GPT. Second, when the search distance exceeds a certain critical point, the cost of extensive search will exceed its value, and corresponding cognitive and management constraints will also be generated (Rosenkopf & Nerkar, 2001; Capaldo & Messeni Petruzzelli, 2011), which hurts GPT innovation. Third, the cognitive ability of an organization to create and integrate knowledge will decrease with increasing cooperation with unfamiliar areas of knowledge because it will reach the apex of the necessary absorptive capacity (Cohen & Levinthal, 1990; Laursen & Salter, 2006). Finally, as search distances increase, firms will gradually focus on familiar knowledge areas to reduce the number and complexity of potential knowledge combinations (Ardito et al., 2016). Thus, some cross-boundary search promotes GPT innovation, while "excessive search" hinders GPT innovation, and thus we propose:

Hypothesis 1. There is an inverted U-shaped relationship between distant search and GPT innovation of firms in emerging industries.

Distant search has a complicated impact on GPT, but the matter is quite different for local search. Local search involves the improvement and development of existing technological knowledge (Cyert & March, 1963; Aharonson & Schilling, 2016), and cannot actuate firms to acquire knowledge of new technology fields. For firms that focus on local search, R&D results can neither spread to other industries nor meet the fundamental characteristics of GPT. In particular, the negative effects of local search would be aggravated, considering the characteristics of "emerging technology fields" mentioned above. As discussed by Fleming and Sorenson (2004), local search may be effective in stable and highly relevant technical fields but may be useless in messy, unstable, and unrelated technical fields. Moreover, according to the resource-based view, the available resources within the specific boundaries of firms are limited, and local search will increase the opportunity seeking cost, which would hinder the firms from accessing diverse knowledge and decrease the possibility of developing GPT innovation (Ardito et al., 2016). Thus, we posit:

Hypothesis 2. Local search has a significant negative effect on the GPT innovation of firms in emerging industries.

In local search strategies, the knowledge bases are similar and there is little or no complementarity of knowledge (Meulman et al., 2018). Firms may be trapped in their own information cocoons, which would hinder GPT innovation. However, if firms can achieve balance in distant and local searches, there would be a positive impact on GPT innovation. As mentioned above, there are inherent complex tensions in the GPT of emerging industries characterized by "emerging technologies + general technologies." While the former characteristic requires firms to conduct distant searches to increase the novelty and uniqueness of knowledge, the latter characteristic requires firms to avoid excessive distant search.

Furthermore, there is also an internal connection and interaction between distant and local search, which will affect the GPT innovation of firms in emerging industries. Specifically, when distant and local searches achieve balance, the development of distant search is conducive to the accumulation of heterogeneous technologies and knowledge, making it more efficient and easier to make further development and transformation based on rich and diverse technical knowledge. On the other hand, local search can help firms achieve significant benefits in the short term, which enables these firms to pursue risky and expensive distant searches (Gupta et al., 2006). In the case of balanced search, distant and local searches can attain self-optimization and mutual reinforcement, spirally promoting GPT innovation. Thus:

Hypothesis 3. Balanced search has a significant positive effect on GPT innovation of firms in emerging industries.

Moderating role of industry alliance heterogeneity

In the emerging industries characterized by knowledge-intensiveness, the innovative resources requested by firms in emerging industries exceed the boundaries of their traditional core capabilities; therefore, industry alliances have become an effective way to move beyond their initial industries to acquire new and external knowledge (Enkel et al., 2018). The knowledge acquisition of firms depends on the knowledge sharing and the interactions among the members within the alliance (Cheng et al., 2022). First, industry alliances create linkages among heterogeneous innovation actors, such as universities, firms, and research institutions. Universities possess profound knowledge and powerful scientific research ability, while research institutions and firms possess sensitivity to technology and market demand. When firms face problems, they can seek help from their industry alliance in a timely fashion (Abbas et al., 2019). Rothaermel and Alexandre (2009) believe that firms can use the complementary capabilities of other alliance members to gain supplements by signing license agreements. Second, firms in emerging industry alliances possessing knowledge heterogeneity can seek technical exchanges and knowledge sharing among members, thus obtaining access to heterogeneous technology resources. Indeed, appropriate heterogeneity promotes technological innovation (Almeida et al., 2003; Datta & Jessup 2013), especially in the GPT field, where multiple technical areas are involved. Finally, industry alliance heterogeneity (not just the heterogeneity among members within a specific industry alliance) plays a more important role. Firms take differentiated industry positions and market areas in different industrial alliances, which affords the alliance a diversified distribution of technology areas and knowledge base reserves, thus enabling firms to complement each other (Grant & Baden, 2004).

In short, the higher the heterogeneity of industry alliances, the more feasibly firms could explore new technology areas to promote GPT innovation, and the lower the likelihood of a narrow focus of local search on known areas and the lower the obstacles to GPT innovation. That is, industry alliance heterogeneity increases the possibility of distant search for cross-border and diverse knowledge acquisition, and also alleviates the negative impact of local search on the innovation of GPT.

However, industry alliance heterogeneity is a double-edged sword for distant search. In the case of high industry alliance heterogeneity, the distant search of firms in emerging industries for heterogeneous and cross-border knowledge may easily damage the mutual understanding among alliance members if it passes a certain boundary, which in turn hinders the exchange and interaction of technical knowledge (Nooteboom et al., 2007; Gilsing et al., 2008). On the other hand, in the case of high industry alliance heterogeneity, the brand-new long-distance knowledge search of firms in emerging industries will push the R&D of technology in a more "alien" way, which causes the R&D activities to gradually deviate from the requirements of "platformality" and "generality" of GPT and limit the application to multiple technical fields. Thus, given enough time, the intrinsic spillover of GPT vanishes and exclusivity arises, thus leading to the decline of innovation of GPT. Thus:

Hypothesis 4. Industry alliance heterogeneity positively moderates the relationship between distant search and GPT innovation.

Hypothesis 5. Industry alliance heterogeneity negatively moderates the relationship between local search and GPT innovation.

Partners' heterogeneous knowledge can improve the absorptive capacity of organizations, reduce unfamiliar knowledge in distant search, and alleviate problems related to understanding the technical and market potential of various knowledge (Hitt et al., 1997). Industry alliance heterogeneity could optimize the impact of a balanced search on the GPT innovation for the following reasons.

First, industry alliance heterogeneity could effectively alleviate the conflict between distant and local search. From the perspective of learning styles, distant search is characterized by research, exploration, experiment, and risk-taking, while local search is characterized by consistency, stability, control, and improvement (Levinthal & March, 1993). Many scholars argue that distant and local searches rely on different organizational routines, abilities, minds, structures, and processes, which generates the inherent inconsistencies and conflicts between distant and local searches. Under such circumstances, an industry alliance can play a great role. On the one hand, as platforms for interaction and selection, industry alliances facilitate the focus firms in either cooperating with existing alliance partners or establishing relationships with new alliance members, which effectively reconciles distant search with local search (Beckman et al., 2004). Furthermore, the industry alliance provides methods of cross-mode decoupling, which can not only preserve the benefits of balance and specialization but also alleviate the disadvantages of conflicting routines and negative transfers, as well as assuage the challenges of tension, complexity and coordination (Stettner & Lavie, 2014).

Second, industry alliance heterogeneity promotes effective interaction between distant and local searches. The sources of knowledge acquired by firms are multi-faceted, and firms in emerging industries can develop technological innovation capabilities through the knowledge of direct and indirect market participants and their interactions (Medase & Abdul-Basit, 2020). Industry alliances create a linkage between the government, industries, universities, and research institutions. While the "universities and research institutions" have a deeper understanding and exploration of basic knowledge theory, as their innovation behavior is more oriented toward basic technology, the "industry" actors' knowledge and technology exploration behavior are more oriented toward commercialization. Thus, the efficiency of distant search among the latter is lower, and an industry alliance provides offset effects. Furthermore, distant search molds the fundamentality of GPT upon which local search allows a targeted transformation and development to shape applied GPT. Therefore, in the case of an industrial alliance with high heterogeneity, local search could be promoted while the firms in emerging industries conduct distant searches, thereby improving the innovation of GPT. Thus:

Hypothesis 6. Industry alliance heterogeneity positively moderates the relationship between balanced search and GPT innovation.

The relationships between knowledge search strategies and GPT innovation are presented in the following theoretical framework in Fig. 1.

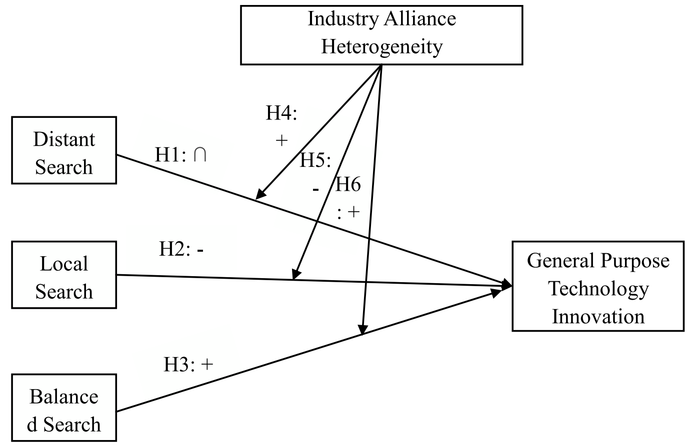

Figure 1. Theoretical Framework

Research design

Sample selection and data collection

Sample identification: As strategic emerging industries often have more cutting-edge technologies and also show more technological connections with other industries (Alkemade & Roald, 2012), they often play a huge leading role in the overall economic and social development. Emerging industries are a development focus in many countries, and have similar characteristics in such countries as the US, Singapore, Japan, and Germany. This study examines seven strategic emerging industries in China: energy conservation and environmental protection, emerging information industry, biological industry, new energy, new energy vehicles, high-end equipment manufacturing, and new materials. Many scholars have carried out extensive research on "strategic emerging industries" and adopted different methods to select samples since the concept was advanced in 2009 in China. The first method is based on the documents issued by the government and the characteristics of strategic emerging industries; for example, Zhao (2014), Fu et al. (2015), and Wu et al. (2018) identified strategic firms in emerging industries according to the "Twelfth Five-Year" National Strategic Emerging Industry Development Plan and Strategic Emerging Industry Classification (2012). The second method refers to analytical literature and government documents; for example, Yan (2016) selected samples based on the research report "National Strategic Emerging Industry Concept Stocks" of China Capital Securities Net and "Status and Characteristics of Strategic Emerging Industry Listed Firms" (2011) of Shenzhen Stock Exchange Institute. The third method, as discussed by Xiao and Wang (2014) and Wu et al. (2017), is selecting "Ping An Strategic Emerging Industries"-listed firms in the Ping An Securities Industry Classification under the WIND Financial Database as initial samples. Considering the consistency and availability of data, the third method was adopted in this paper. After eliminating ST firms, an initial sample was determined as the list of strategic-emerging-industry-listed firms (489 firms total).

Collection of patent data: This paper collects patent data of sample firms according to the firm patent information drawn from the establishment date of the Derwent Innovation Index (DII) to August 26, 2018. The DII is one of the most comprehensive databases of patent information in the world, which is updated in a timely fashion and provides a large number of reliable data sources for patent documents. This paper collected patent information for one month from July 23, 2018, including patent number (PN), international patent classification number (IP), Assignee name or code (AE), citing patents (CP), application details (AD), and designated state/country (DS). Due to the availability of patent data, patent data for a total of 380 firms in emerging industries were searched.

Collection of alliance data: Industrial technology innovation alliances had long not been established in China. Empirical research on industrial alliances has mainly collected data through questionnaire surveys of member firms. This paper uses Yang's (2015) method to collect industrial alliance data by hand, mainly through list collection, including the column of "alliance link" on the "China Industrial Technological Innovation Strategic Alliance" website, the list of documents collected by the Ministry of Science and Technology in 2013 for "The Pilot Industrial Technological Innovation Alliance," and the list of "Zhong Guan Cun Major Industrial Alliance" list. Finally, for this paper, an industry alliance database was constructed that includes 196 firms in 251 strategic emerging industry alliances after four rounds of search. In this paper, the data of the independent and control variables are their average values for 2014, 2015, and 2016. Considering that the outcome of R&D often shows a lag period, the data of the dependent variable, GPT innovation, lag for two years, that is, until 2018. In this paper, the cross-sectional data of 380 firms in emerging industries are the total sample, and the data of 196 firms in emerging industries mentioned above are the sub-sample.

Measurement

(1) Dependent variable: GPT innovation

The existing identification methods for GPT innovation measurement mainly include patent citations (Henderson et al., 1998; Motohashi & Muramatsu, 2012), the technology co-classification ratio

(Luan, 2015), the technology co-classification index (Leydesdorff, 2008; Luan, 2012), and intermediary centrality (Jiang &Wei, 2015; Luan, 2013). Considering the availability of data, this paper adopts both the technology co-classification rate and the technology co-classification index. Due to the lag effect of technological R&D, this paper takes a two-year lag period for GPT innovation.

The technology co-classification ratio (TCR) reflects the co-occurrence between a certain technology field and other technology fields and presents the relatively extensive application of a technology in other technology fields. In the process of calculating the technology co-classification rate, based on the Donohue (1973) model, this paper sets the threshold of the number of co-occurrence partners in the high-frequency technology field of each strategic emerging industry as follows:

$$\mathrm{T} = \frac{-1 + \sqrt{1 + 8\mathrm{I}_1}}{2},$$

where T is the boundary value of high- and low-frequency technology and I_1 is the total frequency. The co-classification rate is calculated according to the co-occurrence matrix, then after selecting high-frequency words to generate the co-occurrence matrix, the co-classification ratio is calculated, such that the higher the technology co-classification rate, the more extensive the penetration of one certain technology field into other technology fields, and thus the higher the GPT innovation. The calculation is as follows:

$$\text{Technology co} - \text{classification Ratio (TCR)} = \frac{\text{Number of co} - \text{occurrence partners}}{\text{Number of all high} - \text{frequency technology fields except itself}}$$

The technology co-classification index (TCI) is a further analysis based on the technology co-occurrence matrix, which reflects the co-occurrence relationship between a particular technology field and other technology fields and the relatively wide degree of application in other technology fields. The higher the co-classification index, the more obvious the "general" characteristics of the technology. In this paper, the Jaccard coefficient matrix is used to calculate the co-classification index between the two technical fields, which is calculated as follows:

$$\mathrm{S(i,j)} = \frac{\mathrm{coo(i,j)}}{\mathrm{occ(i)} + \mathrm{occ(j)} - \mathrm{coo(i,j)}}$$

In this paper, $S(i, j)$ represents the co-classification index of technical fields i and j, $occ(i)$ and $occ(j)$ represent the frequency of co-occurrence of technical fields i and j in the co-occurrence matrix, respectively, and $coo(i, j)$ represents the frequency of co-occurrence of technical fields i and j; the higher the technology co-classification index, the stronger the correlation between a particular technology field and other technology fields, the higher the technological knowledge spillover and the economic value, and thus the higher the GPT innovation.

Considering the differences between industries, the standard for GPT is greater than 0.1 based on the technology co-classification index, and the standard is greater than 30% based on the technology co-classification ratio. Finally, this paper uses the number of GPTs owned by 380 firms to reflect the GPT innovation of firms in emerging industries.

(2) Independent variables

Distant Search (DS): The number of patents that a firm has held over the years is adopted as an indicator of two kinds of knowledge search strategies, and the patent data come from the SOOPAT database. Following Guan and Liu (2016), this paper uses the International Patent Classification (IPC) to measure the distant search, namely, the number of new ICP classification numbers in the first four digits of the approved patents in year t compared with t−5 to t−4 is the number of distant searches performed by firm i in year t. Specific steps are as follows:

The first step is to determine the names of the firms. This paper takes 380 firms with complete patent data in strategic emerging industries as the final sample.

The second step is to determine the type of each patent. Since a design patent hardly involves improvements in the technical field, the patent only includes invention patents and utility model patents.

The third step is to identify "new technology areas." The top four international patent classification (IPC) numbers are used to represent a certain technical field, allowing us to observe whether the firm has entered a certain technical field in the past 5 years, as it is well known that patents have an impact time of 5 years in academic research; if not, the number of patents is considered to be the number of distant searches.

Local Search (LS): The number of patents that firms hold in existing technology fields is used as the number of local searches. To evaluate and measure the distant and local searches comprehensively, this paper takes the average data of local searches for the three years of 2014, 2015, and 2016 as the independent variable.

Balanced Search (BS): There are currently two mainstream measurement methods for balanced search, product term and subtraction term. These two methods reflect different understandings of the relationship between distant and local searches. One view is that distant and local searches are two ends of the knowledge search continuum; thus, researchers generally use "subtraction of the two" to measure search balance. The other view is that distant and local searches conflict with each other, constituting two distinct types of knowledge search; thus many researchers use "multiplying the two" to measure search balance. Based on He and Wong (2004) and Gupta et al. (2006), this paper adopts the former point of view: The subtraction term is used as the measurement of search balance and, as above, the 3-year-average data are used as an indicator for comprehensive evaluation.

(3) Moderator

Heterogeneity (HE): "Heterogeneity of industry alliance" includes regional, cultural, industrial, technological, and other types of heterogeneity of an industry. Here, we mainly refer to the technological heterogeneity of industrial alliances. The technological heterogeneity of industrial alliances refers to the degree of differentiation of alliance partners in terms of technology type and quantity, that is, the distance between partners in the technology space. Richard and Chadwick (2004) and Campbell and Minguez (2008) use the Blau index to determine group diversity, which is suitable for measuring the level of diversity of qualitative variables. Due to the qualitative characteristic of the alliance industry, it is reasonable to use the Blau index to calculate alliance heterogeneity in this paper. It indicates the dissimilarity of each state in the sample from other states, namely, the probability that we randomly selected individuals do not belong to the same sample, which is calculated as follows:

$$BI = 1 - \sum pi^2$$

where p_i represents the proportion of the i-th category in the sample. The closer the Blau coefficient is to 1, the higher the heterogeneity of the industrial alliance, and the closer to 0, the lower the heterogeneity.

(4) Control variables

Corporate financial health (Z-score, Z): The Z-score is an indicator to estimate the financial status of the firm, which sums up five weighted important financial indicators to judge the financial risk status of the firm according to its critical value. These data were directly exported from the Guotai'an database.

Return on Assets (ROA): ROA reflects the efficiency of a firm's use of assets and the ability to use assets to make a profit. Corporate profitability may have an effect on the form of knowledge search, and firms with insufficient profitability may find it difficult to conduct continuous distant searches. Therefore, this paper uses ROA as a control variable. The data were directly exported from the Guotai'an database.

Government Subsidies (GS): The measurement of government subsidies is currently manually collected from a firm's annual reports. For example, Xie et al. (2009) argued that the two accounting subjects related to the government's R&D funding were "subsidy income" and "special payables" by collecting annual reports of listed firms. This paper finds the column of "Government Subsidy" in the database of Tonghuashun, and directly downloads and exports the relevant data of government subsidies from the database.

Financial Leverage (FL): Financial leverage reflects the profitability and leverage of firms. Investment in technological R&D is affected by corporate profitability, and firms with strong profitability and high levels of performance are more inclined to increase technology R&D investment, thus directly promoting the innovation performance of GPT. Therefore, this paper includes financial leverage as a control variable in the model.

Return per Share (EPS): Return per Share (EPS) measures the value of a firm's common stock per share, which reflects its profitability. As a financial performance indicator, the higher the return per share, the stronger the firm's profitability. It is calculated by dividing corporate profits after tax by the number of ordinary shares, and this data is directly derived from the Guotai'an database.

Business Age (AGE): The age of a firm is measured by the difference between the year of observation and the year of registration of the firm, and it has a comprehensive impact on corporate performance. As discussed by Fu (2015), as a firm grows older, its adaptability to the external environment improves its performance, but further growth may lead to conservative trends and a lack of innovation, which in turn hinders the firm. Based on this, this paper takes the age of the firm as a control variable.

Asset Growth Rate (AGR): The asset growth rate reflects the current asset growth of the firm, and the calculation is to divide the difference between the asset of the current period and the asset of the previous period by the asset of the previous period. These data were directly exported from the Guotai'an database.

R&D Intensity (RDI): Considering that the amount of R&D expenditure between different industries and firms cannot be directly compared, this paper uses R&D intensity as a measure of the R&D investment of firms. Generally, the impact of R&D investment on corporate performance is directly reflected in operating income; thus, the ratio of R&D investment to operating income is used to indicate the strength of R&D. Furthermore, the appropriate intensity of R&D investment would help strengthen technological innovation. Therefore, this paper includes R&D intensity as a control variable in the model.

Capital Intensity (CI): Capital intensity reflects the corporate asset structure, and this paper measures capital intensity through the ratio of fixed assets to total assets. Generally, the asset structure largely reflects the firm's ability to pay its debts and secure financing and has an important effect on its technological innovation capabilities. Thus, this paper includes capital intensity as a control variable in the model.

Enterprise Nature (EN): Differences in the nature of property rights cause significant differences in the evolution of a firm and its corporate governance mode, which will affect the innovation performance of the firm. Therefore, this paper controls for the factor of the nature of the firm with the following coding format: 1 = *state-owned enterprise*, 2 = *private enterprise*, 3 = *overseas-funded enterprise*, and 4 = *other* (Liu, 2015). All variables and their measurement methods in this paper are shown in Table 1.

Statistical analysis

We adopt hierarchical regression analysis to test the hypotheses using SPSS software and determine the order in which different variables are entered into the regression equation to test the main effects of knowledge search strategies on GPT innovation and the moderating effect of industry alliance heterogeneity. To

Table 1
Variables and their measurements

Variable type	Variable name (abbreviation)	Variable measurement method	Variable source
Dependent variable	General purpose technologies innovation in emerging industries(GPT)	Identify by technology co-classification index	Luan (2015)
Independent variable	Distant Search (DS)	Measured by International Patent Classification Number	Guan and Liu (2016)
	Local Search(LS)	Measured by International Patent Classification Number	Guan and Liu (2016)
	Balanced Search(BS)	BS=|DS-LS|	Gupta et al. (2006)
Moderator	Hetorogeneity(HE)	Refers to the heterogeneity of the industrial alliance to which the firm joins, as measured by the Blau index	Richard and Chadwick (2004).
Control variable	Z-score(Z)	Z -score = 1. 2*(working capital / total assets) + 1. 4*(retained earnings / total assets) + 3. 3(EBIT / total assets) + 0. 6*(Equity market value / book value of liabilities) +0. 99*(sales / total assets)	Altman(1968))
	Return on Assets(ROA)	Net profit / 2(Total assets at the beginning of the year + Total assets at the end of the year)	Ge (2014)
	Government Subsidies (GS)	Government subsidies that are included in the firm's annual report non-recurring income statement and included in the current profit and loss. As some of the data did not appear in the non-recurring income statement in the annual report, it was supplemented with government subsidy items in non-operating income.	Xie et al. (2009), Han et al. (2016)
	Financial Leverage (FL)	(net profit + income tax expense + financial expenses)/(net profit + income tax expense)	Luo (2018)
	Return Per Share(EPS)	corporate profit after tax / common shares	Li & Zhou (2015)
	Business Age (AGE)	year of observation - year of registration	Tan and Peng (2013)
	Asset Growth Rate(AGR)	the firm's total asset growth this year / total assets at the end of the previous year	Liu (2018)
	R&D Intensity (RDI)	R&D expenses / operating income	Wu (2015)
	Capital Intensity(CI)	fixed assets / total assets	Guo& Cheng (2016)
	Enterprise Nature (EN)	1= state-owned enterprise,2= private enterprise,3= overseas-funded enterprise,4= other	Liu, 2015

Table 2
Descriptive statistics of the total sample***.

variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	VIF
z	0.078	0.120	1												1.025
ROA	0.041	0.049	0.024	1											1.163
AGE	18.250	4.721	0.013	0.089	1										1.044
EN	1.590	0.599	−0.009	0.069	−.141**	1									1.114
CI	3.276	12.791	.127*	−0.057	−0.003	−0.043	1								1.027
AGR	0.413	0.192	−0.012	−.334**	0.094	−.219**	0.071	1							1.251
EPS	0.304	0.554	0.029	−0.056	0.006	−0.048	0.006	0.012	1						1.011
BS	5.749	10.270	−0.066	−.166**	0.084	−.247**	0	.259**	0.035	1					1.135
LS	0.000	12.685	−0.069	−.161**	0.061	−.238**	−0.008	.273**	0.019	.950**	1				5.531
DS	0.000	4.591	−0.042	−0.055	0.053	−.140**	−0.034	.217**	−0.047	.394**	.588**	.333**	1		1.793
GPT	186.82	551.297	−0.013	0.093	−0.013	−.102*	−0.019	.130*	−0.023	.252**	.241**	.126*	0.088	1	1.115

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 3
Descriptive statistics of the sub-sample.

variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13
DS	0.000	.15.817	1												
LS	0.000	5.045	.577**	1											
BS	8.588	13.011	.956**	.413**	1										
HE	.2763097	−.2103271	0.199***	0.0680	0.179**	1									
Z	0.088	0.144	−.209**	−.187**	−.194**	−0.127*	1								
GS	16.866	2.520	0.033	0.018	0.044	0.128*	−0.105	1							
FL	1.318	1.331	0.102	.172*	.149*	0.0750	−0.13	0.013	1						
EPS	0.359	0.699	−0.11	−0.074	−0.105	0.0110	0.026	0.088	−0.064	1					
AGE	16.810	4.922	.142*	0.086	.151*	0.0570	−0.061	−0.099	0.094	0.052	1				
RDS	0.071	0.073	−.195**	−.174*	−.174*	−.00900	.372**	−0.041	−0.134	−0.071	−0.09	1			
AGR	0.237	0.334	−0.14	−0.078	−.140*	−0.0450	−0.031	−0.017	−0.017	0.116	−0.063	0.016	1		
ROA	0.048	0.054	−.249**	−0.086	−.263**	−.00700	.291**	0.021	−.157*	.617**	−0.085	0.002	.229**	1	
GPT	279.640	732.614	.258**	0.057	.270**	0.108	−0.052	.207**	−0.01	.188**	.200**	−0.069	−0.018	0.083	1

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

avoid multicollinearity, variables were normalized before regression analysis.

We build a model to test the effect of distant search, local search, and balanced search on the GPT innovation in emerging industries as follows:

$$GPT = \alpha + \beta 1(distant\ search) + \ \beta 2\ (local\ search) + \beta 3(balanced\ search) + \gamma\ Controls\ + \varepsilon$$

Of these, the independent variable of knowledge search denotes distance search, local search, and balanced search, respectively, and the coefficient β indicates the contribution of each independent variable to the GPT innovation in emerging industries.

To test the moderating effect of industry alliance on the relationship between knowledge search strategies and GPT innovation, a cross-multiplier term is added to the former model:

$$GPT = \alpha + \beta_1(distant\ search) + \beta_2(local\ search) + \beta_3(balanced\ search) + \beta_4 He + \beta_5(distant\ search) * He + \beta_6(local\ search) * He + \beta_7(balanced\ search) * He + \gamma Controls + \varepsilon,$$

where the term “knowledge search * He” denotes (distance search)^2 * He, (local search) * He, and (balanced search) * He, respectively, and the coefficient β_3 shows how industry alliance moderates the effect of knowledge search strategies on the GPT innovation in emerging industries.

Results

Descriptive statistical analysis

The mean, standard deviation, and correlation coefficients of the main variables in the total sample are shown in Table 2. It was found that the square term of distant search and balanced search showed a significant positive correlation with GPT innovation, and Hypotheses 1 and 3 are thus preliminary supported. Moreover, though there are significant correlations between some control variables and the independent variables, there exists no multicollinearity, because the variance inflation factor (VIF) of the variables is lower than 3.

The mean, standard deviation, and correlation coefficient of the main variables in the sub-samples are shown in Table 3. The results show that balanced search and GPT innovation show a significant positive correlation, which supports Hypothesis 3. Moreover, there are significant correlations between some control variables and independent variables, but the variance inflation factor (VIF) of the variables was less than 2, indicative of no multicollinearity.

Hypothesis testing

This paper adopts two-year lagging of the GPT innovation, and to avoid multicollinearity among variables, the interaction term is decentralized. Table 4 presents the regression results for the total sample, while Model 1 is the regression of control variables on the innovation of GPT, on this basis, Model 2 adds distant and local search, Model 3 examines the non-linear relationship between distant search and innovation of GPT, and Model 4 examines the linear relationship between balanced search and innovation of GPT.

Table 4
Analysis of regression results for the total sample.

variable	Model 1	Model 2	Model 3	Model 4
z	−0.011	0.004	0.01	0.005
ROA	0.158***	0.183***	0.184***	0.182***
AGE	−0.054	−0.059	−0.053	−0.066
EN	−0.085	−0.041	−0.03	−0.037
CI	−0.025	−0.022	−0.025	−0.02
AGR	0.171***	0.133**	0.13**	0.126**
EPS	−0.02	−0.027	−0.029	−0.025
DS		0.291***	0.629***	
LS		−0.106*	−0.19***	
DS^2			−0.341***	
BS				0.247***
R^2	0.047	0.101	0.13	0.101
Adjust R^2	0.029	0.079	0.107	0.082
ΔR^2	0.047	0.107	0.03	0.054
ΔF	2.633***	11.029***	12.55***	22.215**
F	2.63	4.61	5.53	5.21
Prob > *F*	0.0115	0.0000	0.0000	0.0000

Note: The dependent variable is GPT.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 5 shows the regression result for the sub-sample of 196 firms in emerging industries for which there is complete information about the alliance. This paper introduces "industry alliance heterogeneity (HE)" as a moderator in the sub-sample regression, and examines the moderating role of industry alliance heterogeneity between search strategies and GPT innovation. The sub-sample includes the main effect test and the moderation effect test, and the main effect test is consistent with the results for the total sample.

Taking the sub-sample results as an example for analysis, while Model 6 shows that local search has a significant negative effect on the innovation of GPT (β= −0.177, $p < 0.05$), namely, the stronger the local search, the weaker the performance of GPT, so Hypothesis 2 is supported; Model 7 shows that the squared term of distant search has a significant negative effect on GPT innovation (β = −0.355, $p <$ 0.01), meaning there is an inverted U-shaped relationship between distant search and GPT innovation, so Hypothesis 1 is supported; Model 8 shows that balanced search has a significant positive effect on GPT innovation (β = 0.29, $p < 0.01$), such that balanced search could avoid "failure traps" and "success traps" at the same time, which helps promote GPT innovation, so Hypothesis 3 is supported; Model 9 shows that industry alliance heterogeneity promotes the effect of distant search on the GPT innovation (β = 0.23, $p < 0.05$), so Hypothesis 4 is supported; Model 10 shows a negative effect of industry alliance heterogeneity on the relationship between local search and GPT innovation (β = −0.13, $p < 0.1$), such that the more types of industries in the alliance that a firm joins, the more types of external technical support and knowledge that firm can access, which can alleviate the negative effect of local search on the innovation of GPT, so Hypothesis 5 is supported; and Model 11 shows that alliance heterogeneity positively moderates the relationship between balance search and GPT innovation (β = 0.182, $p < 0.1$), so Hypothesis 6 is supported.

Robustness tests

To verify the robustness of the regression results, this paper adopts three robustness tests.

(1) Robustness test 1: Replacement of the samples

This paper has two batches of samples, namely 380 firms and 196 firms, both of which could be used to test the main effect; and the results of these main effect tests are consistent. Distant search and GPT innovation have an inverted U-shaped relationship, local search has a negative effect on GPT innovation, and balanced search has a positive effect on innovation of GPT. The results are shown in Tables 4 and 5.

(2) Robustness test 2: Replacement of control variables

Replacing ROA with ROE, R&D intensity with R&D expenses, deleting EPS, and performing regression again, the results are shown in Table A1 of the Appendix. It can be seen that distant search and GPT innovation show an inverted U-shaped relationship (β = −0.333, $p <$ 0.01), local search negatively affects GPT innovation (β = −0.181, $p <$ 0.05), balanced search positively affects GPT innovation (β = 0.233, p < 0.01), the interaction terms of distant search squared terms and

Table 5
Analysis of regression results for the sub-sample.

variable	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Z	−0.018	−0.007	−0.005	0.003	0.005	0.008	−0.003
GS	0.212***	0.201***	0.155**	0.119***	0.182***	0.16**	0.221***
FL	−0.023	0.024	0.041	−0.018	0.045	0.025	−0.01
EPS	0.153*	0.132	0.115	0.143	0.092	0.144*	0.119
AGE	0.211***	0.176**	0.179***	0.174**	0.204***	0.184***	0.189***
RDI	−0.027	0.009	0.034	0.008	0.03	0.004	0.006
AGR	−0.021	−0.005	−0.004	0.001	0.003	−0.008	0.001
ROA	0.007	0.094	0.116	0.075	0.125	0.077	0.085
LS		−0.177**	−0.26***		−0.279***	−0.196	
DS		0.381***	0.727***		0.792***	0.409***	
DS^2			−0.355***		−0.576***		
BS				0.29***			0.216***
HE					−0.047	0.039	−0.061
HE*DS^2					0.23**		
HE*LS						−0.13*	
HE*BS							0.182*
R^2	0.118	0.203	0.239	0.193	0.26	0.218	0.21
Adjust R^2	0.081	0.159	0.193	0.153	0.207	0.166	0.163
ΔR^2	0.118	0.084	0.036	0.074	0.021	0.014	0.016
ΔF	3.125**	9.731**	8.637**	17.000**	5.025***	3.303***	3.716**
F	3.12	4.68	5.22	4.91	4.89	4.22	4.43
Prob > *F*	0.0024	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: The dependent variable is GPT.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

industry alliance heterogeneity, and the interaction terms of balanced search and industry alliance heterogeneity are positively correlated with innovation of GPT ($\beta = 0.261$, $p < 0.05$; $\beta = 0.19$, $p < 0.05$), and the interaction terms of local search and industry alliance heterogeneity are negatively correlated with the innovation of GPT ($\beta = -0.118$, $p < 0.1$). In short, the direction and significance of the regression results are basically consistent with the main model after replacing some control variables. The results are shown in Table A1 of the Appendix.

(3) Robustness test 3: Replacement of dependent variable

This paper uses another measure of the GPT-technology co-classification ratio instead of the technology co-classification index, and the results of the re-regression are shown in Table A2 of the Appendix. It can be seen that distant search and innovation of GPT show an inverted U-shaped relationship ($\beta = -0.421$, $p < 0.01$), local search has a negative effect on GPT innovation ($\beta = -0.18$, $p < 0.05$), balanced search has a positive correlation with innovation of GPT ($\beta = 0.21$, $p < 0.01$), the interaction terms of the distant search square term and industry alliance heterogeneity, and balanced search and industrial alliance heterogeneity have a positive correlation with innovation of GPT ($\beta = 0.222$, $p < 0.1$; $\beta = 0.125$, $p < 0.1$), and the interaction between local search and alliance heterogeneity is negatively correlated with performance of GPT ($\beta = -0.147$, $p < 0.05$). In short, the direction and significance of the regression results are basically consistent with the main model after replacing the dependent variable. The results are shown in Table A2 of the Appendix.

Based on the above three robustness test results, the regression results obtained by different regression models are basically consistent with the direction and significance of the main model. Therefore, it can be said that the results in this paper show good robustness.

Discussion

First, GPT in an emerging industry can be characterized as showing both “generality” and “emergence,” requiring firms to make trade-offs in knowledge search. As discussed in Section 2.1, research on knowledge search has emphasized the impacts of different knowledge search strategies on technological innovation, which may be caused by such factors as firm nature, differences in the technical scope of the search, and cognitive distance between firms. Our results show that distant knowledge search has a significant inverted U-shaped relationship with GPT innovation, local knowledge search negatively affects GPT innovation, and balanced knowledge search is positively correlated with GPT innovation. These results are all statistically significant, indicating that knowledge search strategies are critical to technological innovation and revolution.

Second, the heterogeneity of industry alliances has a moderating effect in the relationship between knowledge search strategy and GPT innovation. Generally speaking, governments and industries consider alliances an important source of original ideas for innovation. Industries can gain relevant knowledge (solution) from collaborating in alliances, saving cost and time related to R&D activities (Abbas et al., 2019). When firms lack knowledge, they can seek to join different types of alliances. On the one hand, firms can obtain resources helpful for R&D through technical knowledge sharing and other cooperation activities within the alliance. On the other hand, through knowledge transfer and knowledge creation between alliance members (Bouncken et al., 2016), firms can improve their technological capability through knowledge heterogeneity and alliance management experience. The acquisition of such resources and capabilities can help firms improve GPT innovation.

Third, considering that many factors affect the relationship between knowledge search strategies and GPT innovation, we set the firm’s financial condition (ROA and AGR) as controls in our regression model. In the regression results for the total sample, we see that the coefficients of ROA and AGR are positively significant. In particular, though we used a sample from China, we controlled for variables with obvious Chinese characteristics, including government subsidies (GS) and the nature of firms (EN). Government subsidies (GS) may have a certain crowding-out effect on innovation within firms (Zhu et al., 2020), leading to decreased distant knowledge search and increased local knowledge search. The nature of firms (EN) is also controlled to reduce the impact of the research context, which may affect firms’ enforcement of government policy.

Finally, firms have been actively adopting knowledge search strategies for innovation. Since firms in emerging industries are characterized by large R&D investments and high R&D risks, most firms tend to protect their intellectual property through patents. If high-tech firms in emerging industries can reasonably use knowledge search strategies, they can overcome this routine locking effect and improve GPT innovation. Our findings are consistent with those of Nosella (2014), who examined Italian companies to find that technological innovation did not differ from country to country, but showed certain commonalities. As to knowledge search for innovation, lo Storto (2006) found that firms conduct local searches for technological innovations in a short period, and are more inclined to distant searches over a longer period, which is also supported by our empirical results.

Conclusions

Research conclusions

From the perspective of knowledge, this paper examines the impact of knowledge search on the GPT innovation of firms in emerging industries, taking 380 firms in emerging industries as the total sample and 196 firms as the sub-sample, drawing the following conclusions: (1) Different knowledge search strategies have differential effects on the GPT innovation in emerging industries. Specifically, there is an inverted U-shaped relationship between distant search and GPT innovation, a negative relationship between distant search and GPT innovation, and a positive relationship between balanced search and GPT innovation; and (2) the heterogeneity of an industry alliance positively moderates the relationship between distant search, balanced search, and GPT innovation, and negatively moderates the relationship between local search and GPT innovation.

Theoretical contributions

The theoretical contributions of this paper are as follows.

(1) This paper investigates GPT innovation based on the perspective of knowledge search by focusing on the inherent complex tensions of GPT in emerging industries, as well as responding to the call to focus on “search” research in this field.

GPT in emerging industries shows the dual characteristics of “emerging technology + general technology,” and plays an increasingly important role in the development of emerging industries, as well as the overall technological progress of society and the development of the national economy (Devezasa et al., 2005; Strohmaier & Rainer, 2016). This paper analyzes the inherent complex tensions between “generality” and “emerging” based on the characteristics of “GPT in emerging industries,” and examines GPT innovation through an ambidextrous perspective of distant/local search. On the one hand, it responds to the call to “examine the general technology supply of firms from the role of organizational search strategies” (Thoma, 2009). On the other hand, it also expands the shortcomings of most studies that focus on “search breadth” (such as Rosenkopf & Nerkar, 2001; Argyres & Silverman, 2004; Banerjee & Cole, 2010; Novelli, 2015; Ardito et al., 2016).

(2) This paper investigated the role of the heterogeneity of industry alliances in the relationship between knowledge search and GPT

innovation in emerging industries, transcending the focal-agent view of existing research.

Many studies have examined the multi-agent characteristics of general technology R&D process, including government (such as Raiteri, 2018), competitors (such as Gambardella & Giarratana, 2013), R&D institutions (such as Barirani et al., 2017), industry-university-research (such as Fan et al., 2018), and parasitic technologies (Coccia & Watts, 2020). Based on the natural characteristics of cross-border and cross-industry GPT (Andergassen et al., 2017), this paper examines the role of industrial alliances in optimizing the knowledge search strategies of firms in emerging industries to improve GPT innovation in emerging technologies. On the one hand, it expands the scope of the "main body of R&D" of existing general technology research. On the other hand, it also examines the role and mechanism of distant/local search and its balance on the GPT innovation in emerging industries

Implications and shortcomings

The management implications of this paper are as follows. First of all, firms in emerging industries need to pay attention to knowledge search strategies when conducting GPT innovation, and in particular, they should avoid confining technology searches to inherent knowledge areas. Second, when trying to use a distant search strategy for GPT innovation, firms in emerging industries should consider the "degree" and "boundary" of distant search, maintain distant search at an optimal level, and thereby promote GPT innovation as much as possible. Third, firms in emerging industries can try to strike a balance between local search and distant search to effectively use the advantages of both knowledge search strategies at the same time, thereby improving GPT innovation. Finally, the heterogeneity of the industry alliances in which firms in emerging industries participate can effectively promote the advantages of distant and balanced search strategies and alleviate the disadvantages of local search strategies. Therefore, when firms in emerging industries join an industrial alliance, they not only need to pay attention to the number and size of the alliance but also take the heterogeneity and diversity of the alliance into account. By balancing the three search strategies, firms can gain better performance in GPT innovation, thus responding to the demands of firms to identify and explore new technology opportunities (Porter & Detampel, 1995), to achieve and sustain the prospect of a (temporary) profit monopoly (Coccia, 2017).

There are some shortcomings in this paper. First of all, in the measurement of general purpose technologies in emerging industries, the measurement is mainly based on the co-classification matrix, and the characteristics of the overflow of general technology are ignored. Second, due to the limitations of the calculation, the general technology database constructed in this paper cannot replicate panel data, which poses a certain challenge to the conclusions of this paper. Finally, we chose the samples from China, which might have generated deviations from the results for other countries.

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Appendix

Table A1, Table A2.

Table A1
Regression results of robustness test 2.

variable	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
Z	−0.017	0.008*	0.018	0.031	0.026	0.028	0.009
GS	0.212***	0.207***	0.162**	0.252***	0.198***	0.126*	0.227***
FL	−0.024	0.018	0.031	−0.001	0.032	0.033	−0.016
AGE	0.21***	0.171**	0.173**	0.203***	0.198***	0.181***	0.186***
RD	−0.027	0.006	0.027	−0.012	0.025	0.024	0.004
AGR	−0.022	−0.01	−0.003	−0.007	0.003	−0.007	−0.006
ROE	0.016	0.138	0.117	0.166	0.134	0.107	0.144
LS		−0.181**	−0.253***		−0.278***	−0.268***	
DS		0.392***	0.709***		0.794***	0.721***	
DS^2			−0.333***		−0.584***	−0.319***	
BS				0.233***			0.225***
HE					−0.042	0.036	−0.063
HE*DS^2					0.261**		
HE*LS						−0.118*	
HE*BS							0.19**
R^2	0.119	0.206	0.238	0.276	0.259	0.223	0.215
Adjust R^2	0.081	0.163	0.192	0.232	0.205	0.172	0.167
ΔR^2	0.119	0.087	0.032			0.02	0.017
ΔF	3.127***	10.101**	7.635***			4.955**	3.906**
F	3.13	4.77	5.19	6.34	4.86	4.64	4.54
$Prob > F$	0.0024	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: The dependent variable is GPT.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table A2
Regression results of robustness test 3.

variable	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24	Model 25
Z	−0.041	−0.031	−0.028	0.006	−0.024	−0.014	−0.022
GS	0.211***	0.201***	0.146**	0.234***	0.176**	0.155**	0.212***
FL	0.019	0.066	0.086	0.052	0.088	0.068	0.031
EPS	0.144	0.123	0.102	0.059	0.079	0.136	0.117
AGE	0.169***	0.135*	0.139**	0.169**	0.161**	0.144**	0.144**
RDI	−0.01	0.025	0.056	−0.02	0.054	0.021	0.023
AGR	−0.012	0.004	0.005	0.011	0.01	0	0.01
ROA	−0.01	0.077	0.103	0.069	0.115	0.058	0.064
LS		−0.18**	−0.279***		−0.301***	−0.202**	
DS		0.382***	0.793***		0.867***	0.414***	
DS^2			−0.421***		−0.637***		
BS				0.21***			0.238***
HE					−0.037	0.041	−0.029
HE*DS^2					0.222*		
HE*LS						−0.147**	
HE*BS							0.125*
R^2	0.1	0.184	0.235	0.266	0.25	0.203	0.184
Adjust R^2	0.061	0.14	0.189	0.222	0.196	0.151	0.135
ΔR^2	0.1	0.084	0.051	0.049	0.015	0.018	0.008
ΔF	2.581***	9.526**	12.129***	12.324**	3.562**	4.15***	1.709**
F	2.58	4.16	5.11	6.03	4.65	3.87	3.74
$Prob > F$	0.0108	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001

Note: The dependent variable is GPT.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

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