Technological Forecasting & Social Change 119 (2017) 80–97

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

Using the data mining method to assess the innovation gap: A case of industrial robotics in a catching-up country

Dejing Kong [a,b,c], Yuan Zhou [b,*], Yufei Liu [d], Lan Xue [b]

[a] School of Modern Post, Beijing University of Posts and Telecommunications, Beijing, China
[b] School of Public Policy and Management, Tsinghua University, Beijing, China
[c] The CAE Center for Strategic Studies, Chinese Academy of Engineering, Beijing, China
[d] College of Life Science and Technology, Huazhong University of Science and Technology, Wuhan, China

ARTICLE INFO

Article history:
Received 20 September 2016
Accepted 20 February 2017
Available online 18 March 2017

Keywords:
Innovation gap assessment
Support vector machines-based classifier
High-quality patents
Industry robot
China

ABSTRACT

It is critical for "catching-up" countries to narrow innovation gaps with developed countries by developing emerging industries. This research introduces a data-mining based method to systematically assess the national innovation gap that is specifically for emerging industries. The method examines the five key attributes of emerging industries, including the ownership of platform technologies, globalization intention, international knowledge position, university-industry linkage, and cross-disciplinary technology development. In particular, this method combines data-mining with experts' knowledge to build patent-training examples, and then uses a support vector machine-based classifier to single out all high-quality patents for each innovation attribute. Based on the selected high-quality patents, the authors utilize a factorial design analysis to systematically evaluate the innovation gap between countries. This method can significantly reduce measurement bias of traditional single patent indicators. In addition, it also can robustly adjust measuring weights in response to the specifics of each innovation attribute, while traditional multi-attribute evaluation methods cannot. As a result, this research empirically shows that China' industrial robot sector has apparent innovation gaps compared to developed economies, specifically in university-industry linkage, cross-disciplinary competence, and globalization intention, and this calls for the attention of policy makers and industrial experts.

1. Introduction

Innovation is necessary for "catching-up" countries (Fan, 2006). Backward countries – at different times – have managed to narrow the gap in innovation between themselves and the frontier countries, and we call it "catch up". Studies have noted that innovation is a major stimulus for national economic growth in industrial, newly industrialized, and developing economies (Archibugi et al., 1991; Ernst and Kim, 2002; Guan and Chen, 2012; Kim, 1980; Pavitt and Walker, 1976). Further, an effective diffusion of innovation is vital for the economic development of many countries' operating periods under different social and economic systems (Guan et al., 2005). Every country is a beginner in the newly emerging techno-economic paradigm, and innovation capability can serve as a cause for catching up (Schumpeter, 1942). Latecomers can catch up with more advanced countries by leap-frogging, or direct innovation at the technological frontier. Shortening the innovation gap with developed countries is meaningful, as well as achieving leaps in development, by developing emerging industries to facilitate this catch-up (Perez, 2010).

Multiple methods exist to assess innovation and innovation gaps across entities, using a variety of attributes as noted in Table 1. Innovation is a comprehensive result of multiple factors, and it is difficult to evaluate innovation based only on objective data. Thus, the case study is a popular method to illustrate innovation capability and the gap between latecomers and frontiers (Hobday, 1998; Fan, 2006; Fu et al., 2011; Choung et al., 2014; Rogo et al., 2014; Gao, 2015; Ernst, 2015). A survey-based quantitative analysis is another effective method to evaluate innovation capability and this gap (Anderson et al., 2013; Forés and Camisón, 2016; Guan and Yam, 2015; Vecchi and Brennan, 2009; Wu et al., 2016; Zehir et al., 2015). The results through case

Abbreviations: AHP, analytic hierarchy process; CN, China; CTD, cross-disciplinary technology development; DWPI, Derwent World Patents Index; EPO, European Patent Office; GE, Germany; GI, globalization intentions; HighValue, high-quality patent counts; IKP, international knowledge positions; INPADOC, International Patent Documentation Center; IPC, International Patent Classification; JP, Japan; JPO, Japan Patent Office; KR, South Korea; LDA, Latent Dirichlet Allocation; OPT, ownership of platform technologies; PCT, Patent Cooperation Treaty; Percentage, percentage of high-quality patents in all patents in a country; SVM, support vector machine; TI, Thomson Innovation; UIL, university-industry linkages; US, the United States; USPTO, United States Patent and Trademark Office.

* Corresponding author.
E-mail addresses: zhou_yuan@mail.tsinghua.edu.cn, zhouyuan.joseph@gmail.com (Y. Zhou).

http://dx.doi.org/10.1016/j.techfore.2017.02.035
0040-1625/

Table 1
Attributes to assess innovation for the emerging industry.

Assessing attribute	Studies by case study on innovation			Studies by survey on innovation			Studies by econometrics on innovation		
	Fan (2006)	Rogo et al. (2014)	Gao (2015)	Guan and Yam (2015)	Forés and Camisón (2016)	Wu et al. (2016)	Corrocher et al. (2003)	Fu and Yang (2009)	Liu and Zhi (2010)
Ownership of platform technologies	*		*	*				*	*
Globalization intention						*	*		
international knowledge position		*	*		*				*
University-industry linkage	*	*	*		*		*	*	*
Cross-disciplinary technology development		*					*		

Assessing attribute	Studies by econometrics on innovation		Studies by bibliometrics on innovation						
	Li et al. (2016)	Castellacci and Natera (2016)	Porter and Detampel (1995)	Hung and Chu (2006)	Srinivasan (2008)	Bekkers and Martinelli (2012)	Wu and Mathews (2012)	Ávila-Robinson and Miyazaki (2013)	Li et al. (2016)
Ownership of platform technologies						*	*	*	*
Globalization intention	*	*							
International knowledge position		*	*			*	*	*	*
University-industry linkage			*	*	*		*	*	*
Cross-disciplinary technology development				*	*		*		

study or survey methods can be easily affected by the selection of cases and interviewees. Another type of quantitative method is based on patents, journal publications, news, and economic data that focus on innovation capability and diffusion efficiency (Ávila-Robinson and Miyazaki, 2013; Castellacci and Natera, 2016; Fu and Yang, 2009; Gu et al., 2016; Li et al., 2016; Liu and Zhi, 2010; Mellor and Hyland, 2005; Oura et al., 2016; Shao and Lin, 2016; Wu and Mathews, 2012).

Patent data can effectively indicate innovation performance, including product, process, and technology innovation, which is especially more accurate than such alternative measures as "new product" sales (Acs et al., 2002; Choi et al., 2011; Fu, 2008; Hong and Su, 2013; Jaffe et al., 1993; Usai, 2011; Wang and Lin, 2013). Previous research has always selected one single indicator, or a package of single indicators, to indicate various countries' innovation capabilities based on patent data, such as citations (Guan and Gao, 2009; Harhoff et al., 2003; Liu and Zhi, 2010), the number of publications (Fu and Yang, 2009), claims (OuYang and Weng, 2011; Tong and Frame, 1994), and the number of countries in which the patents are filed (Ernst and Omland, 2011; Harhoff and Hoisl, 2007; Meyer et al., 2011), among others. These indicators are always easily obtainable patent features, and they assume that the patent's quality or quantity can be presented by one indicator in one dimension. However, quality is a comprehensive effect achieved through different patent features. Multi-criteria methods also exist to indicate innovation, such as the analytic hierarchy process (AHP), and these can compare different countries' patent portfolios using different indicators' weights, measured by expert assessment. However, the real case is complicated, caused by multiple technology categories of owned patents, multiple countries that have prioritized patents, and multiple time periods in which the patents were published. The weights differ under various conditions, and the mass data characteristics cannot be adequately and comprehensively processed in batch mode.

Therefore, this research proposes a new method, support vector machines (SVMs), to identify high-value patents and assess innovation gaps between different countries based on high-quality patents. This is a popular and effective supervised-learning method, which asks a machine or algorithm to learn from the training sets for patent classification (Venugopalan and Rai, 2015). Experts can select a set of training examples in one classification (including two categories: one positive and one negative category) based on expert knowledge, which is similar to using more complex composited indicators. Not all high-quality patents require expert selection, while all of the patents in the positive category can be guaranteed as high quality. Similarly, all of the patents in the negative category can be guaranteed as low quality. When an expert identifies whether a patent is high quality, he considers multiple patent features, with different resulting contributions. However, no fixed weights exist for different features, such as traditional AHP methods. The contributions of features regarding high-quality patents' identification are more flexible to reflect experts' knowledge. Additionally, SVMs have the absolute advantage in handling massive amounts of data.

This research will use SVMs to assess innovation gaps between late-development and developed countries, and use a factorial design analysis to investigate the direction in which more investments are necessary (Beck-Broichsitter et al., 2012; Macdonald, 2011) in an empirical study of industrial robot innovation. Industrial robotics is a compelling, emerging, and important enabling technology, with radical novelty and relatively fast growth, coherence, prominent impacts, and uncertainty (Rotolo et al., 2015). This industry receives increasing attention with manufacturing developments, especially when it proposed that integrating artificial intelligence, robotics, and digital manufacturing technology was revolutionizing manufacturing. China is a late-developing country in industrial robotics compared with the United States, Japan, and Germany. This study's goal is to evaluate the innovation gap between leading industrial robotics countries and late-development countries by integrating SVMs based on patent data to address the following questions:

Q1: Does the SVM-based method provide reliable and valid innovation assessment results?
Q2: How large are the industrial robotics innovation gaps among the United States, Japan, Germany, and China?
Q3: How can the industrial robotics innovation gap change for China?
National innovation is a comprehensive performance related to multiple attributes. The authors measure an emerging industry's innovation gap between late-developing and developed countries through an assessment from five perspectives: the ownership of platform technologies, globalization intentions, international knowledge positions, university-industry linkages, and cross-disciplinary

technology development. Displaying a country's overall situation is more comprehensive and systemic than using patent counts from the European Patent Office (EPO) or triadic patent family counts, which can only reveal the patent situation of the country or assignee. The article is structured as follows to achieve its goals: the second section will introduce the research's detailed methodology. The third section will review the technical narrative of industrial robotics from experts' perspectives, which introduce the empirical case to verify the research methodology's effectiveness. The fourth section provides the empirical analysis, and the fifth section discusses and concludes.

2. Methodology

Most prior research focused on innovation assessment has been based on multiple attributes and specific indicators to indicate both innovation capacity and efficiency (Fan, 2006; Forés and Camisón, 2016; Fu and Yang, 2009; Shao and Lin, 2016). This article proposes the introduction of support vector machines (SVMs) for data mining to assess the innovation gap between China and developed countries based on patent data (See Fig. 1), which can ignore the bias of specific indicators.

2.1. Support vector machines-based machine learning

Patenting is considered a representative activity for an empirical analysis of innovation. Patents are the direct outcome of the inventive process, and because of the cost and time involved in patenting, a commercial benefit can be expected, thus leading to innovation (Pianta and Archibugi, 1996). Further, they are publicly available, and as they are not covered by confidential clauses, time-series data can be obtained. Although patents have strength as representative tools, not all lead to innovation (Caillaud and Duchêne, 2011; Cohen et al., 2002). Thus, the authors utilized machine learning to split the patents into those from the patent database that make greater contributions to innovation in deep-data mining for innovation gap assessments, which the authors call "high-quality patents" in the research.

Support vector machines (SVMs) in machine learning are supervised learning models with associated learning algorithms that analyze data used for classification and regression analyses (Cortes and Vapnik, 1995). Compared with other machine learning classifiers, such as neural networks, quadratic and linear discriminant analyses, or Latent Dirichlet Allocation (LDA), SVMs can demonstrate advanced performance in several classification tasks, and have the best accuracy for patent categorizations (Joachims, 1998; Venugopalan and Rai, 2015).

A SVM training algorithm given a set of training examples, each marked to one of two categories (one positive and one negative category), builds a model that assigns new examples into one category or the other, as a non-probabilistic binary linear classifier. A SVM model represents the examples as points in space, mapped so that the separate categories' examples are divided by a clear gap, which is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on to which side of the gap they fall (Harrington, 2012).

Assume a training dataset in feature space is

$$T = \{(x_1, y_1), (x_2, y_2), \ \ldots, (x_N, y_N)\},$$

where $x_i \in \chi = R^n$, $y_i \in \Upsilon \in \{+1, -1\}$, $i = 1, 2, \ldots, N$, x_i is the ith p-dimensional real vector, and y_i is the class marker of x_i. When $y_i = +1$, x_i is a positive example; when $y_i = -1$, x_i is a negative example. The classifier must discover the "maximum-margin hyperplane" that divides the group of points $\vec{x_i}$, for which $y_i = +1$, from the group of points for which $y_i = -1$. This is defined to maximize the distance between the hyperplane and the nearest point $\vec{x_i}$ from either group. The hyperplane can be written as a set of points $\vec{x_i}$ satisfying

$$\omega^* \cdot x + b^* = 0,$$

where ω^* is the (not necessarily normalized) normal vector to the hyperplane, and b^* indicates the intercept. The corresponding classification decision function can be written as

$$f(x) = sign(\omega^* \cdot x + b^*).$$

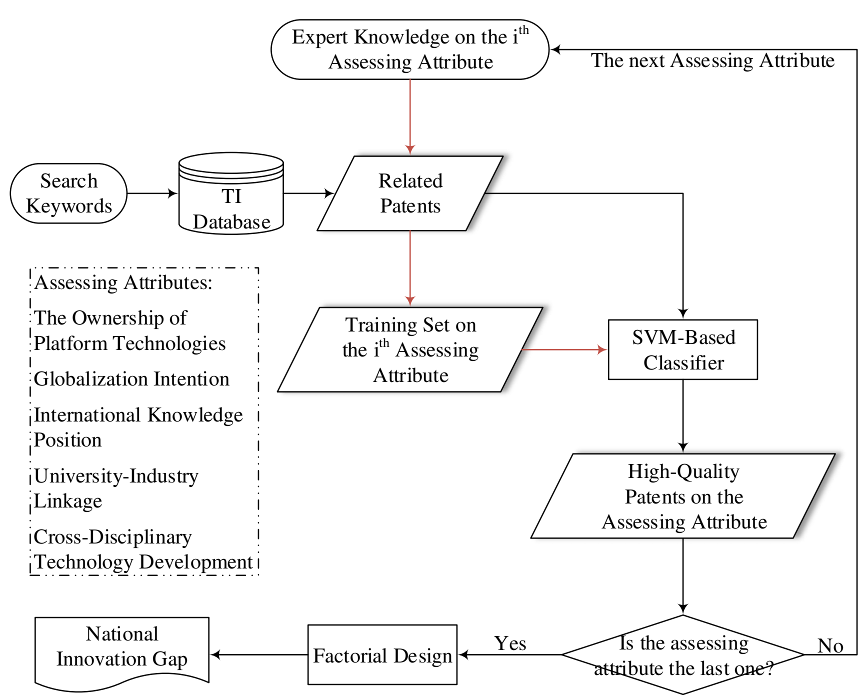

Fig. 1. The framework for innovation gap assessment.

2.2. Assessing attributes for the emerging industry

Innovation attributes in the emerging industry must be identified to complete the innovation gap assessment. Several perspectives based on the literature review evaluate innovation and the gap between developed countries and latecomers, such as R&D input (Ernst, 2016; Gu et al., 2016; Liu and Zhi, 2010; Rogo et al., 2014; Wu et al., 2016), innovation capability (Fan, 2006; Forés and Camisón, 2016; Fu and Yang, 2009; Shao and Lin, 2016), and innovation efficiency (Fu and Yang, 2009; Shao and Lin, 2016). Researchers have always focused on the causal relationship between R&D inputs and innovation capability when assessing R&D input gaps. This research focuses on the gap of innovation itself between countries, regardless of the R&D input. Thus, five critical attributes have been recognized in Table 1: the ownership of platform technologies, globalization intention, international knowledge position, university-industry linkages, and cross-disciplinary technology development.

Finally, the authors utilize a factorial design analysis to investigate the innovation gap across countries. This is a widely utilized method in engineering optimization and decision sciences (Beck-Broichsitter et al., 2012; Macdonald, 2011; Onsi, 1975), which could potentially be introduced in innovation science. A factorial design analysis is popular for the development of new products as well as product or process improvement, and this can improve with the combined factors of high quality, high production, and low consumption through fewer tests. One country's innovation can be treated as the product in this research, and attribute, time period, and country can be assessed as the factors. The innovation gap across countries can be assessed by comparing output with different country factor levels.

2.2.1. Ownership of platform technologies

The ownership of platform technologies is one level used to assess attribute factors. Technological innovation is a key element in industrialization, and catch-up in developing countries (Fu et al., 2011). A knowledge-based economy has more potential for the sustainable development than an extensive economy with high energy consumption and pollution, and low productivity. The technology push theory (Nemet, 2009) notes that advances in scientific understanding determine innovation's rate and direction. Technology is treated as the source of innovation, as well as a motivation for innovators, and platform technology is the core of a specific industry. A platform is a group of technologies used as a base upon which other applications, processes, or technologies are developed. A patent analysis of platform technologies' ownership is an effective method to analyze the trajectories and innovation in platform technologies (Ernst, 2003).

2.2.2. Globalization intention

Globalization intention provides another level in assessing attribute factors. Global intellectual property is critical for global, sustainable competitiveness (Gosens and Lu, 2014), and a patent's geographic extent is proportional to an innovation's success (Grimaldi et al., 2012). As this framework aims to analyze the innovation gap between countries, the authors have decided to evaluate geographic coverage and protection by considering both the dimension and quality of markets. According to Ernst (2001), a patent reaches high-value innovation when it is granted at the USPTO (United States Patent and Trademark Office), EPO, and the JPO (Japan Patent Office).

2.2.3. International knowledge position

International knowledge position is a third level in assessing attribute factors. Less-developed countries require substantial time to reach the same technology frontier as innovation-driven economies. During this process, they can reduce the technology gap and catch up by absorbing external knowledge from technologically leading nations through various knowledge interactions (Guan et al., 2005). The role of knowledge flow has been emphasized both in theoretical arguments and empirical studies (Cowan and Jonard, 1999; Schilling and Phelps, 2007). Several studies have focused on how social network structure influences the flow of knowledge, and how network positioning has affected the actor's innovation performance (Cowan and Jonard, 1999; Uzzi and Spiro, 2005; Schilling and Phelps, 2007; Bettencourt et al., 2009). A patent analysis can help assess this position from an international knowledge perspective (Grimaldi et al., 2012).

2.2.4. University-industry linkage

University-industry linkage is the fourth level in assessing attribute factors. Scientific linkage is critical to assess the quality of knowledge and build internalization capabilities, and is particularly essential for latecomers (Hu and Mathews, 2008). Increasingly, patents are citing scientific literature, and particularly with emerging new technologies. Thus, a high scientific linkage indicates that a patent is building on a technology base grounded in scientific advances (Wu and Mathews, 2012). National governments prefer to improve the link between the research activities in universities and research institutes, and the national economy's needs (Liefner, 2003). Many governments have cut public funding, and have encouraged universities to obtain research funds from commercialization, such as through contract research (Gibbons, 1994). The gap between universities and research institutes' knowledge supply and industries' knowledge demand is much wider in developing countries than in those that are developed (Liu and Zhi, 2010). An assessment of the innovation gap is meaningful from the university-industry linkage perspective.

2.2.5. Cross-disciplinary technology development

Cross-disciplinary technology development is the fifth level in assessing attribute factors. Numerous monographs and anthologies underline the importance of cross-disciplinary research on innovation, and especially for future and emerging technology, in considering the complexity of global problems (Hadorn et al., 2007; Lyall et al., 2011). Future and emerging technologies are science-driven, large-scale, and multidisciplinary research initiatives oriented towards a unifying goal, with a transformational impact on science and technology, and substantial benefits. Many studies have found that boundary-spanning communication in networked organizations can be beneficial. For example, workers in a diverse network, which consists of members with heterogeneous knowledge and expertise from various work units, may access various resources outside their silo, which assist in creating innovation (Cox and Blake, 1991; Herring, 2009; Jehn and Neale, 1999; Kilduff and Mehra, 2000).

3. A technical narrative of industrial robotics

What is an industrial robot? How does one define it? Even scholars struggle to answer these questions. ISO defines an industrial robot in two ways: a "manipulating industrial robot — automatically controlled, reprogrammable, multi-purpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation application," and a "mobile robot — which carries all of the means needed for its monitoring and movement (power control and driving)" (IFR, 2013a; IFR, 2013b; IFR, 2013c). The industrial robot is one of the most important pieces of automation equipment in the advanced manufacturing factory.

3.1. Worldwide industrial robotics development

The modern industrial robot was first developed in the middle of the 20th century, relying on the rapid development of computers, automation, and atomic energy (Sun and Luo, 2012). Much nuclear radiation was generated in the processing of atomic energy, which was significantly harmful to the human body. The United States' Argonne Institute developed the tele-operation manipulator in 1947 to solve this problem (Graefe and Bischoff, 2009), as well as a mechanical master-slave manipulator in 1948 (Hitachi, 2008), to perform operations with radioactive substances in radioactive environments, rather than humans. Meanwhile, to satisfy the urgent demands for large quantities of product manufacturing, a numerically-controlled machine tool was created in 1952 (Carlsson, 1984), with the development of related automation technologies. The development of key NC machine tool components, such as a control system, servo motor, and reducer, provided a solid foundation for the development of industrial robotics.

Devol and Engelberger (Wang and Tao, 2014) invented the first reprogrammable and industrial robots in the 1950s, and they applied the patents later. The United States' AMF Ltd. in 1962 launched VERSATRAN, a versatile transfer machine that was one of the earliest practical industrial robots (Robotworx, 2013). Its control system was similar to NC machine tools', while its appearance approximated a human, with arms and hands. The Massachusetts Institute of Technology developed a type of robot system in 1965 with integrated visual sensors to identify and position simple bricks (Torgny, 2007). The first International Industrial Robots Conference was held in the United States to promote the development of robotics research in 1970, and consequently, industrial robotics research widened and development quickly occurred.

Japan founded its Manipulator Research Association in 1967, and held its first academic robotics conference (IFR, 2012). Kawasaki Heavy Industries, Ltd., introduced robotics products and technologies from the United States in 1967, and established production plants. The company then developed Japan's first general robotic manipulator in 1968 (Jone, 2013). Japan promoted the use of robots in various fields, which could ease social conflicts from serious labor shortages, and industrial robotics came into its prime in Japan from 1980 to 1990. Assembly and logistics-handling robots came into use in the 1990s (IFR, 2011).

As typical advanced manufacturing equipment, the industrial robot has become a measure of a country's manufacturing level, and an important symbol of scientific and technological development. Multi-fields have widely utilized the industrial robot in their production since the 1960s, through such methods as automobile and automotive component manufacturing; the machinery-processing, electrical, and electronics industries; the rubber and plastics industry; the food industry; logistics; and manufacturing to improve processing efficiency and product consistency (Xu and Yan, 2012). The market scale of global industrial robotics since 1960 has been approximately \$10 billion to \$12 billion through its 50-year development, and annual sales have approached 160,000 sets (Zhao, 2012). Japan and Europe have significant advantages in industrial robots' research and production, with many well-known corporations, such as the ABB Group, the KUKA Robotics Corporation, FANUC, and Yaskawa, which cover 60% to 80% of the industrial robotics market share. Technological innovation in robotics is active in the United States, as it has absolute advantages in the military, medical, and domestic service robot industries.

3.2. Chaotic period in China (before 1985)

China is a latecomer to the industrial robotics industry, as Chinese scholars had the first understanding of robot technologies in the early 1970s from foreign magazines; robotics research first appeared at this time. However, research and development was restrained, disordered, and sporadically spontaneous due to outdated information and the stagnation of academic exchanges in China.

Universities and research institutions in the 1980s conducted several robotics research and development projects, as well as engineering application and development projects, under the support of the National Scientific and Technological Commission, military departments, and local governments. Gradually, a variety of robot technology research centers and their corresponding academic institutions were formed. The Shenyang Institute of Automation of the Chinese Academy of Sciences, one of the best robotics research institutes in China, began planning a robotics engineering center supported by the SSTC in 1982, and it was established in 1984, primarily to develop both intelligent and underwater robots (Cao and Xie, 2008).

During this period, the development of robotics in China was characterized by: (1) spontaneous research, with separately generated topics; (2) only a robot prototype existed, and the robot prototypes' control systems were directly copied and simple; and (3) robotics organizations were found in universities and scientific research institutes.

3.3. Primary planning stage in China (1986 to 2000)

Chinese scholars and governments had recognized the importance of industrial robotics in the mid-1980s, and the Chinese government arranged its "Industrial Robot Development Research Project" as a significant national scientific research project in the Seventh Five-Year Plan (1986 to 1990). The Mechanical and Electrical Ministry was responsible for implementing this project, authorized by both the National Planning Commission and National Economic Commission. China had formed a technical team for the research and development of robot technologies through the project's implementation, and built a solid foundation for the sustainable development of China's industrial robot technologies.

The central government released its "High Technology Research and Development Program" in 1986, and a committee of automation experts established two themes under the program (Wang, 2007): a computer-integrated manufacturing system and intelligent robotics. The National Science and Technology Commission held a signing ceremony for "cooperation agreement on robots and automation application engineering" on August 24, 1995, which marked the end of adjustments for the second stage of strategic targeting in the intelligent robotics theme (Cao and Xie, 2008).

The research, development, and application of robot technology in China evolved in this period (1986 to 2000), from spontaneous and decentralized to organized and systemic, and many robotics achievements occurred in the efforts of government departments, academic organizations, and all scientific and technical personnel. China had successfully developed three genres and five models of robots during the Seventh Five-Year Period, and had conducted preliminary application trials. However, a large gap of original technology innovation still existed between China and developed countries regarding robotics and automation equipment.

3.4. Preliminary industrialization development in China (2001 to 2010)

Several domestic robotics companies were established in China at the end of the 20th and beginning of the 21st centuries, benefiting from the 863 national program implementations from 1986 to 2000. Most of the companies were founded by universities or research institutes, such as the Shenyang Siasun Robot Automation Corporation, fostered by Shenyang Institute of Automation of the Chinese Academy of Sciences; Harbin Boshi Robot Corporation, by the Harbin Institute of Technology; and Tianjin Nankai Taiyang Corporation, by Nankai University, among others. The robot industry began to take shape in this period.

Robotics experts in 863 national programs adjusted the robot technology development strategy in 2001. The central task had been simple robot technology research, and this changed after 2001, to "research and develop robot manufacturing cells and systems, automation equipment, and special robots for advanced manufacturing; to promote the intellectualization of traditional machines and the development of the robotics industry; and to improve the overall level of automation technology in China" (Wang, 2007). After this adjustment, a strategic layout centered on "national strategic equipment and core competitive technology," and "overall national strength improvement and enterprise competitiveness." The strategy's core task involved developing robotics enterprises and the industry.

China's economy and technology had gained significant progress through its reform and opening over more than 20 years, and China was prepared to develop its industrial robotics industry. During the Eleventh Five-Year Period (2006 to 2010), industrial robotics development focused on the automation technology for complete sets of equipment, and its application in integrated circuits, ships, automobiles, textiles, household appliances, and food. This innovation and development aimed to break through foreign companies' monopoly on large-scale automation manufacturing systems, as well as promote the industrialization of robot technology, and it achieved some successes.

3.5. Explosive development in China (after 2011)

The "Intelligent Manufacturing Technology Development in the Twelfth Five-Year Plan" and "Service Robot Technology Development in the Twelfth Five-Year Plan" have indicated that the industrial robotics industry was a key strategic emerging industry in China. The country's manufacturing industry is currently transforming from labor-intensive to modernized, and China's industrial robotics market has displayed vigorous development as the first largest market in Asia. The demand for Chinese industrial robotics has rapidly increased since 2010; active service robots in China accounted for 9% globally in 2015, and there were 75,000 industrial robots in the market, with a year-on-year growth of 36.6%.

The development of the robotics industry in China was slow, with weak domestic innovation capabilities, and eminently relied on imported key components. Interminably, the industry and economy's development depended on a low labor force and scale expansion, production techniques were relatively outdated, and industrial robotics' application development was limited. From a market share perspective, international brands accounted for over 85% of products (Song and Yao, 2015). Although nearly 60 domestic enterprises were engaged in industrial robot production in China, such as Siasun, Boshi, Aifute, and GSK, their products had low industrialized application levels, with a production scale of only dozens of industrial robots.

The government's work report and development plan declared in 2014 that the robotics industry was a priority development area in China to promote its innovation development. Further, the central government released its "Robotics Industry Development Plan, 2016–2020" to accelerate its development. The document is meaningful in guiding government departments and enterprises to realize industrial robotics' innovation and development, and to shorten the innovation gap in this industry between China and developed countries.

4. Empirical analysis

The authors utilized Thomson Innovation (TI) to create a patent database on industrial robotics in June 2016, with 155,532 patents included in the innovation gap assessment research. The company's well-known database platform captures worldwide patents, and TI's patents are rewritten according to their standards by its staff. The authors developed a search strategy with robotics experts, using accuracy and completed-cover as criteria. The search strategy for industrial robotics included many technologies, searched by International Patent Classification (IPC) and Derwent World Patent Index (DWPI) number, and multiple products, searched by keyword.

4.1. Data

Fig. 2 illustrates that a small crest occurs in patent development for industrial robots in the 1980s, and a larger crest is currently forming; this general trend conforms to industrial robot development. Japan devoted itself to industrial robot development in the 1980s to relieve pressure from labor shortages (Kumaresan and Miyazaki, 1999), and currently, advanced production strategies aiming at intelligent manufacturing has attracted worldwide attention. Industrial robotics, as a pivotal clasp in advanced manufacturing, again ushers in new development opportunities. Approximately 18 months are spent on patent data collection from different countries and standardization for TI staff, and the hysteresis of collection may cause declines in 2015 and 2016.

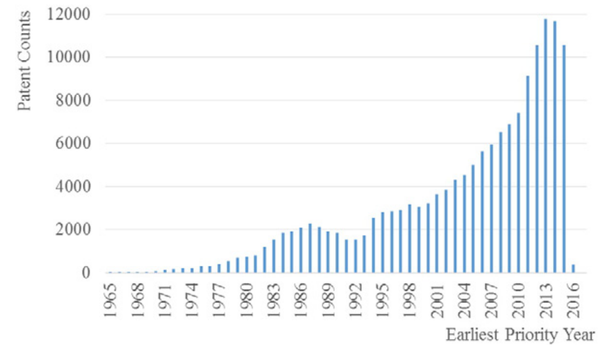

Fig. 2. Descriptive statistics of patents in the database.

Twenty-seven fields are loaded in the patent database to sign the patent records, based on availability noted by TI and correlation with the five attributes. The fields include priority year, publication number, claims count, assignee/applicant, assignee-DWPI, assignee count, inventor — w/address, inventor count, publication kind code, priority country, earliest PCT app number, PCT pub date, IPC — current full (4 characters), IPC class, DWPI class, count of cited refs — patent, count of cited refs — non-patent, count of citing patents, INPADOC legal status code, reassignment date (US), designated states, litigation (US), publication language, DWPI count of family members, DWPI count of family countries, assignee — standardized, and application country.

The numbers of patents announced by the five main countries are displayed in Fig. 3: China (CN), the United States (US), Germany (GE), South Korea (KR), and Japan (JP). These five countries are selected due to their manufacturing strength, emphasis on industrial robotics, and coverage in almost all of the patents, based on Section 3.

Fig. 3 indicates that China's number of patents has rapidly increased since 2004, and the other four countries' patents have slowly increased since 1980. The hysteresis of TI's collection may cause declines in 2015 and 2016.

4.2. SVM-based classification

The authors have organized three meetings to collect experts' opinions from the industrial robotics field regarding the selection of training sets. Experts identify whether a patent can be a positive or negative training example by reading all information provided in TI's database, such as the abstract, text, citation information, family information, legal status, and priority information. Five training sets respectively pertain to the ownership of platform technology (OPT), globalization intentions (GI), international knowledge position (IKP), university-industry linkage (UIL), and cross-disciplinary technology development (CTD), which are utilized in SVMs to split the patents from the database that more greatly contribute to industrial robotics development.

The authors run 50 replicates of classifications for each attribute to assure the algorithm's stability, and the training set is randomly separated into two parts in each replicate. Of the patents randomly selected from the training set, 70% are for training, and the remaining 30% of patents are for testing to detect the learning accuracy rate.

Table 2 demonstrates that the United States and Japan always have the most high-quality patents in every assessed attribute. Although there are few high-quality patents, Germany's percentage of high-quality patents is obviously higher than China and South Korea, except in CTD.

4.2.1. Ownership of platform technology analysis

The core and frontier platform technologies in industrial robotics include electric actuators, electric servo drives, intelligent sensors, and

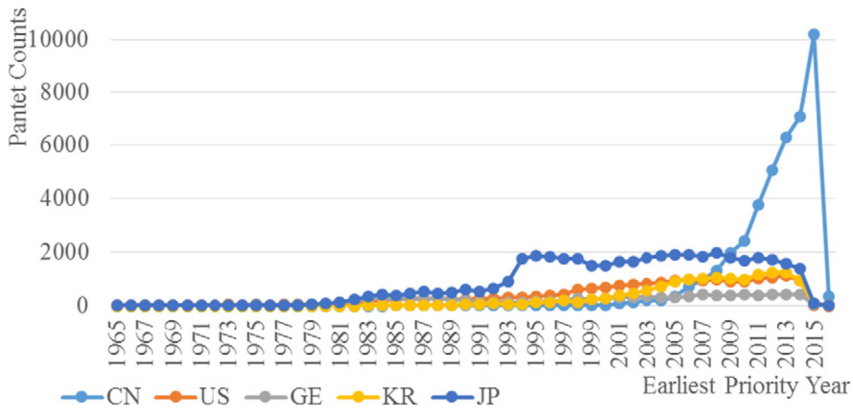

Fig. 3. Patent counts of main countries in the database.

precious reducers (Kumaresan and Miyazaki, 1999). The training set consists of 108 patents noted as valuable to platform technology innovation, and 502 patents were noted as valueless to platform technology development. The 95% confidential interval of accuracy rate, based on the 50 replicates' machine learning results, is (0.975, 0.981). Table 3 displays inconsistent contribution degrees for different features, while a feature's contribution coefficient does not directly determine the causal relationship between the feature and one patent's quality. The factors that can influence this relationship include feature encoding, training example selections, and algorithm and parameter selections, among others. However, common features are included that relate to patent quality regarding the ownership of platform technologies, such as the number of citing patents, with coefficients equaling 9.237; the DWPI number of family members, with 3.989; application country, with −2.095; IPC current full (4 characters), with −2.020; and publication language, with −1.499.

4.2.2. Globalization intention analysis

The training set has 485 patents noted as valuable to the innovation of globalization intentions, and 469 patents are noted as valueless to globalization development. The 95% confidential interval of accuracy rate, based on the 50 replicates' machine learning results, is (0.982, 0.986). Table 3 indicates that although the features' contribution coefficients in the classification do not present a causal relationship between the feature and patent quality, common features are included that relate to the patent quality for globalization intention, such as the DWPI number of family countries, with a coefficient of 6.961; application country, with −2.388; number of citing patents, with 1.857; INPADOC legal status code, with −0.652; and DWPI number of family members, with 0.538.

4.2.3. International knowledge position analysis

The training set noted 506 patents as valuable to the innovation of international knowledge position, and 846 noted as valueless for the ascent. The 95% confidential interval of accuracy rate, based on the 50 replicates' machine learning results, is (0.982, 0.986). Table 3 illustrates that although the features' contribution coefficients for the classification do not present a causal relationship between the feature and patent quality, the common patent quality features for international knowledge position include the number of citing patents, with a coefficient equaling 33.626; DWPI number of family members, with 2.713; publication language, with −2.208; publication kind code, with −1.063; and number of cited refs − patent, with 0.615.

Table 2
Descriptive statistical results of SVM classifiers.

Assessing attribute	Country	Average high-quality patent counts	Percentage of high-quality patents
Ownership of platform technologies (OPT)	China (CN)	1943	4.70%
	the United States (US)	10,067	49.97%
	Germany (DE)	3111	31.04%
	South Korea (KR)	1220	8.50%
	Japan (JP)	12,053	27.52%
Globalization intention (GI)	China (CN)	1217	2.94%
	the United States (US)	15,873	78.78%
	Germany (DE)	6279	62.65%
	South Korea (KR)	2841	19.79%
	Japan (JP)	36,006	82.20%
International knowledge position (IKP)	China (CN)	10,533	25.49%
	the United States (US)	13,213	65.58%
	Germany (DE)	5185	51.74%
	South Korea (KR)	3876	27.00%
	Japan (JP)	22,593	51.58%
University-industry linkage (UIL)	China (CN)	10	0.02%
	the United States (US)	3786	18.79%
	Germany (DE)	999	9.97%
	South Korea (KR)	243	1.69%
	Japan (JP)	2201	5.03%
Cross-disciplinary technology development (CTD)	China (CN)	396	0.96%
	the United States (US)	8824	43.80%
	Germany (DE)	2470	24.65%
	South Korea (KR)	4099	28.56%
	Japan (JP)	26,001	59.36%

Table 3
Contribution degrees of classified patent features.

Average contribution degree on the classification result		Assessing attributes				
		OPT	GI	IKP	UIL	CTD
Features of patents in TI database	Publication number	−0.112	0.028	0.082	−3.555	−0.632
	Assignee/applicant	−0.244	0.035	−0.864	−7.735	0.098
	Publication kind code	−0.376	0.139	−1.063	−9.084	−0.798
	Inventor — w/address	−0.567	0.055	−0.173	−5.909	0.023
	DWPI class	0.104	−0.187	−0.112	−0.411	0.019
	Assignee — DWPI	−0.038	0.198	−0.388	0.076	−0.286
	Inventor count	−0.655	0.006	−0.386	−5.525	0.244
	Assignee count	0.256	0.034	−0.348	−1.269	−0.657
	Count of cited refs — non-patent	0.154	−0.010	0.083	14.360	−0.106
	Count of citing patents	9.237	1.857	33.626	0.013	0.045
	Count of cited refs — patent	−0.016	−0.027	0.615	2.532	0.020
	IPC class	0.457	0.092	−0.237	−1.704	−1.070
	IPC current full (4 characters)	−2.022	0.056	−0.164	−6.267	0.982
	Priority country	−0.688	0.049	−0.514	−4.198	0.921
	PCT pub date	0.000	0.000	0.000	0.000	−0.013
	Designated states	0.386	0.092	−0.155	2.957	0.147
	Claims count	−0.701	0.255	0.284	1.348	0.031
	Assignee — standardized	−0.020	0.198	−0.380	−1.515	−0.269
	Application country	−2.095	−2.388	−0.548	0.108	−0.731
	PCT app number	0.000	0.000	0.001	0.000	−0.013
	INPADOC legal status code	−0.555	−0.652	−0.203	−2.201	0.006
	Reassignment (US) — date	−0.134	0.030	−0.185	−4.254	−0.406
	Litigation (US)	0.002	0.000	0.003	−0.023	0.000
	Language of publication	−1.499	0.007	−2.208	−2.202	0.247
	DWPI count of family members	3.989	0.538	2.713	16.328	0.727
	DWPI count of family countries	−0.129	6.961	−0.069	0.178	−0.033

4.2.4. University-industry linkage analysis

The training set noted 478 patents as valuable to the innovation of university-industry linkage, and 332 patents noted as valueless to strengthen the linkage. The 95% confidential interval of accuracy rate, based on the 50 replicates' machine learning results, is (0.913, 0.926). Table 3 demonstrates that although the features' contribution coefficients for the classification do not present a causal relationship between the feature and patent quality, the common patent quality features for university-industry linkage include the DWPI number of family members, with a coefficient equaling 16.328; number of cited refs — non-patent, with 14.360; publication kind code, with −9.084; assignee/applicant, with −7.735; and IPC current full (4 characters), with −6.267.

4.2.5. Cross-disciplinary technology development analysis

The training set noted 376 patents as valuable to the innovation of cross-disciplinary technology development, and 665 patents were noted as valueless for cross-disciplinary development. The 95% confidential interval of accuracy rate, based on the 50 replicates' machine learning results, is (0.771, 0.797). Table 3 reveals that although the features' contribution coefficients for the classification do not present a causal relationship between the feature and patent quality, the common features related to the patent quality for cross-disciplinary technology development include IPC class, with a coefficient equaling −1.070; IPC current full (4 characters), with 0.982; publication kind code, with −0.798; DWPI number of family members, with 0.727, and assignee count, with −0.657.

4.3. Innovation gap between catching-up countries and developed countries

The authors utilize a general full-factorial design analysis from Minitab 17 in this research to assess the innovation gap between catching-up and developed countries. National innovation in the industrial robotics industry is the output, with different combinations of factor levels to assess attributes, time periods, and countries. Five levels are used to assess attributes: the ownership of platform technology (OPT), globalization intentions (GI), international knowledge position (IKP), university-industry linkages (UIL), and cross-disciplinary technology development (CTD). Four time periods are used: before 1985 (marked as 1), 1986–2000 (2), 2001–2010 (3), and after 2011 (4). The boundary years for each time period are included in their period, and the time periods are set based on industrial robotics industry development in China. Five country levels are included: China (CN), the United States (US), Germany (GE), South Korea (KR), and Japan (JP). There are 50 replicates in the factorial design.

This analysis indicates innovation through the worldwide count of priority patents in the high-quality category from SVMs. This is because the worldwide quantity of priority patents is proven as an effective indicator of inventive activity (de Rassenfosse et al., 2013). Further, the percentage of high-quality patents out of all priority patents is another indicator in research studies to neutralize time period-length effects.

4.3.1. Cross-country innovation gaps

The R^2-adjusted for the factorial analysis using high-quality patent counts (HighValue) to indicate innovation is 95.19%, and the R^2-adjusted using a percentage of high-quality patents (Percentage) is 92.42%. Both of the R^2-adjusted are sufficiently large, and the factorial analysis results are acceptable. The analysis of variance (ANOVA) table and the differences in HighValue and Percentage between the different factor and interaction levels are significant.

The coefficient tables indicate several exceptions, in which the factor or interaction levels are insignificant for innovation. Regarding the HighValue analysis: Percentage in the second time period does not have significant differences among countries for international knowledge position, with a P-value of 0.243. Further, the United States does not indicate significant differences among different time periods for university-industry linkages, with a P-value of 0.173. Regarding the Percentage analysis: HighValue in the first stage does not display significant differences among countries from the globalization intentions and university-industry linkages perspectives, with P-values of 0.295 and 0.431, respectively. South Korea does not indicate significant differences among different time periods for the ownership of platform technology, with a P-value of 0.386. Further, China does not reveal significant differences among different assessing attributes in the second time period,

Table 4
General full factorial design analysis results.

General factorial regression: HighValue versus Attributes, Stage, Country

Analysis of variance

Source	DF	Adj SS	Adj MS	F-value	*P*-value
Model	99	46,222,000,029	466,888,889	980.04	0
Linear	11	26,567,175,516	2,415,197,774	5069.69	0
Attributes	4	4,842,363,729	1,210,590,932	2541.12	0
Stage	3	7,928,112,757	2,642,704,252	5547.24	0
Country	4	13,796,699,029	3,449,174,757	7240.08	0
2-Way interactions	40	15,868,203,695	396,705,092	832.71	0
Attributes * Stage	12	1,950,184,480	162,515,373	341.13	0
Attributes * Country	16	6,016,093,540	376,005,846	789.27	0
Stage * Country	12	7,901,925,675	658,493,806	1382.23	0
3-Way interactions	48	3,786,620,818	78,887,934	165.59	0
Attributes * Stage * Country	48	3,786,620,818	78,887,934	165.59	0
Error	4900	2,334,359,467	476,400		
Total	4999	48,556,359,496			

Adjusted R-squared = 0.951
Coefficients

Term	Coef	SE Coef	T-value	*P*-value	VIF
Constant	1950.4	9.76	199.81	0	
Attributes					
OPT	−530.7	19.5	−27.18	0	1.6
GI	1160.4	19.5	59.44	0	1.6
IKP	819.6	19.5	41.98	0	1.6
UIL	−1588.4	19.5	−81.36	0	1.6
Stage					
1	−1551.8	16.9	−91.79	0	1.5
2	599.2	16.9	35.44	0	1.5
3	1725.6	16.9	102.07	0	1.5
Country					
CN	−1245.5	19.5	−63.8	0	1.6
US	637.8	19.5	32.67	0	1.6
DE	−1048.2	19.5	−53.69	0	1.6
KR	−1336.5	19.5	−68.46	0	1.6
Attributes * Stage					
OPT 1	548.1	33.8	16.21	0	2.4
OPT 2	210.9	33.8	6.24	0	2.4
OPT 3	−406.3	33.8	−12.02	0	2.4
GI 1	−941	33.8	−27.83	0	2.4
GI 2	333	33.8	9.85	0	2.4
GI 3	740.3	33.8	21.89	0	2.4
IKP 1	−671.7	33.8	−19.86	0	2.4
IKP 2	39.5	33.8	1.17	0.243	2.4
IKP 3	881.5	33.8	26.07	0	2.4
UIL 1	1263.1	33.8	37.36	0	2.4
UIL 2	−570.5	33.8	−16.87	0	2.4
UIL 3	−1367.5	33.8	−40.44	0	2.4
Attributes * Country					
OPT CN	311.6	39	7.98	0	2.56
OPT US	459.4	39	11.76	0	2.56
OPT DE	406.2	39	10.4	0	2.56
OPT KR	221.7	39	5.68	0	2.56
GI CN	−1561.2	39	−39.98	0	2.56
GI US	219.7	39	5.63	0	2.56
GI DE	−492.9	39	−12.62	0	2.56
GI KR	−1064.1	39	−27.25	0	2.56
IKP CN	1108.8	39	28.4	0	2.56
IKP US	−104.6	39	−2.68	0.007	2.56
IKP DE	−425.5	39	−10.9	0	2.56
IKP KR	−464.7	39	−11.9	0	2.56
UIL CN	886	39	22.69	0	2.56
UIL US	−53.2	39	−1.36	0.173	2.56
UIL DE	935.9	39	23.97	0	2.56
UIL KR	1035.3	39	26.52	0	2.56
Stage * Country					
1 CN	847.1	33.8	25.05	0	2.4
1 US	−206.5	33.8	−6.11	0	2.4
1 DE	1034.4	33.8	30.59	0	2.4
1 KR	938	33.8	27.74	0	2.4
2 CN	−1275.4	33.8	−37.72	0	2.4
2 US	229.7	33.8	6.79	0	2.4

Table 4 (*continued*)

General factorial regression: HighValue versus Attributes, Stage, Country

Analysis of variance

Source		DF	Adj SS	Adj MS	F-value	*P*-value
2 DE	−186	33.8	−5.5	0	2.4	
2 KR	−986.3	33.8	−29.17	0	2.4	
3 CN	−908.3	33.8	−26.86	0	2.4	
3 US	255.4	33.8	7.55	0	2.4	
3 DE	−1110.7	33.8	−32.85	0	2.4	
3 KR	−614.7	33.8	−18.18	0	2.4	
Attributes * Stage * Country						
OPT 1 CN	−329.2	67.6	−4.87	0	3.84	
OPT 1 US	−259.9	67.6	−3.84	0	3.84	
OPT 1 DE	−383.4	67.6	−5.67	0	3.84	
OPT 1 KR	−239.3	67.6	−3.54	0	3.84	
OPT 2 CN	9.6	67.6	0.14	0.887	3.84	
OPT 2 US	469.9	67.6	6.95	0	3.84	
OPT 2 DE	29.7	67.6	0.44	0.661	3.84	
OPT 2 KR	−6	67.6	−0.09	0.929	3.84	
OPT 3 CN	598	67.6	8.84	0	3.84	
OPT 3 US	349.8	67.6	5.17	0	3.84	
OPT 3 DE	203.6	67.6	3.01	0.003	3.84	
OPT 3 KR	23.3	67.6	0.34	0.731	3.84	
GI 1 CN	1341.6	67.6	19.84	0	3.84	
GI 1 US	−98.7	67.6	−1.46	0.145	3.84	
GI 1 DE	497.4	67.6	7.36	0	3.84	
GI 1 KR	844.5	67.6	12.49	0	3.84	
GI 2 CN	51.1	67.6	0.76	0.45	3.84	
GI 2 US	−459.2	67.6	−6.79	0	3.84	
GI 2 DE	−311.6	67.6	−4.61	0	3.84	
GI 2 KR	−441	67.6	−6.52	0	3.84	
GI 3 CN	−1105.8	67.6	−16.35	0	3.84	
GI 3 US	17.2	67.6	0.25	0.799	3.84	
GI 3 DE	−298.1	67.6	−4.41	0	3.84	
GI 3 KR	−769.2	67.6	−11.37	0	3.84	
IKP 1 CN	−1255.9	67.6	−18.57	0	3.84	
IKP 1 US	233	67.6	3.44	0.001	3.84	
IKP 1 DE	496.4	67.6	7.34	0	3.84	
IKP 1 KR	316.6	67.6	4.68	0	3.84	
IKP 2 CN	−1899.2	67.6	−28.08	0	3.84	
IKP 2 US	242.1	67.6	3.58	0	3.84	
IKP 2 DE	249.3	67.6	3.69	0	3.84	
IKP 2 KR	−294.3	67.6	−4.35	0	3.84	
IKP 3 CN	829.4	67.6	12.26	0	3.84	
IKP 3 US	−177.3	67.6	−2.62	0.009	3.84	
IKP 3 DE	−554.2	67.6	−8.2	0	3.84	
IKP 3 KR	85.9	67.6	1.27	0.204	3.84	
UIL 1 CN	−560.9	67.6	−8.29	0	3.84	
UIL 1 US	−220.3	67.6	−3.26	0.001	3.84	
UIL 1 DE	−932.4	67.6	−13.79	0	3.84	
UIL 1 KR	−710.2	67.6	−10.5	0	3.84	
UIL 2 CN	1244.8	67.6	18.41	0	3.84	
UIL 2 US	−51.7	67.6	−0.76	0.445	3.84	
UIL 2 DE	227.4	67.6	3.36	0.001	3.84	
UIL 2 KR	916.6	67.6	13.55	0	3.84	
UIL 3 CN	551.6	67.6	8.16	0	3.84	
UIL 3 US	152.8	67.6	2.26	0.024	3.84	
UIL 3 DE	1009.8	67.6	14.93	0	3.84	
UIL 3 KR	384.7	67.6	5.69	0	3.84	

General factorial regression: Percentage versus Attributes, Stage, Country

Analysis of variance

Source	DF	Adj SS	Adj MS	F-value	*P*-value
Model	99	496.66	5.0168	616.71	0
Linear	11	366.98	33.3614	4101.12	0
Attributes	4	137.41	34.3529	4223.01	0
Stage	3	24.58	8.1933	1007.21	0
Country	4	204.98	51.2459	6299.67	0
2-Way interactions	40	114.72	2.8681	352.57	0
Attributes * Stage	12	24.15	2.0123	247.37	0
Attributes * Country	16	77.58	4.849	596.08	0
Stage * Country	12	12.99	1.0827	133.1	0
3-Way interactions	48	14.96	0.3117	38.32	0
Attributes * Stage * Country	48	14.96	0.3117	38.32	0

(continued on next page)

Table 4 (*continued*)

General factorial regression: Percentage versus Attributes, Stage, Country

Analysis of variance

Source		DF	Adj SS	Adj MS	F-value	*P*-value
Error		4900	39.86	0.0081		
Total		4999	536.52			
Adjusted R-squared		0.9242				
Coefficients						
Term	Coef	SE Coef	T-value	*P*-value	VIF	
Constant	0.34611	0.00128	271.35	0		
Attributes						
OPT	−0.06207	0.00255	−24.33	0	1.6	
GI	0.20146	0.00255	78.97	0	1.6	
IKP	0.14519	0.00255	56.91	0	1.6	
UIL	−0.26759	0.00255	−104.89	0	1.6	
Stage						
1	−0.01254	0.00221	−5.68	0	1.5	
2	0.0622	0.00221	28.16	0	1.5	
3	0.06004	0.00221	27.17	0	1.5	
Country						
CN	−0.23961	0.00255	−93.93	0	1.6	
US	0.28747	0.00255	112.69	0	1.6	
DE	0.06886	0.00255	26.99	0	1.6	
KR	−0.22173	0.00255	−86.92	0	1.6	
Attributes * Stage						
OPT 1	0.07951	0.00442	18	0	2.4	
OPT 2	0.0563	0.00442	12.74	0	2.4	
OPT 3	−0.01892	0.00442	−4.28	0	2.4	
GI 1	−0.03198	0.00442	−7.24	0	2.4	
GI 2	−0.04904	0.00442	−11.1	0	2.4	
GI 3	−0.01096	0.00442	−2.48	0.013	2.4	
IKP 1	0.00462	0.00442	1.05	0.295	2.4	
IKP 2	0.0773	0.00442	17.5	0	2.4	
IKP 3	0.07494	0.00442	16.96	0	2.4	
UIL 1	−0.00348	0.00442	−0.79	0.431	2.4	
UIL 2	−0.05813	0.00442	−13.16	0	2.4	
UIL 3	−0.04007	0.00442	−9.07	0	2.4	
Attributes * Country						
OPT CN	0.04901	0.0051	9.61	0	2.56	
OPT US	0.06174	0.0051	12.1	0	2.56	
OPT DE	0.01325	0.0051	2.6	0.009	2.56	
OPT KR	−0.00443	0.0051	−0.87	0.386	2.56	
GI CN	−0.26092	0.0051	−51.14	0	2.56	
GI US	0.14594	0.0051	28.6	0	2.56	
GI DE	0.11142	0.0051	21.84	0	2.56	
GI KR	−0.18592	0.0051	−36.44	0	2.56	
IKP CN	0.12656	0.0051	24.81	0	2.56	
IKP US	0.02913	0.0051	5.71	0	2.56	
IKP DE	0.03422	0.0051	6.71	0	2.56	
IKP KR	−0.08818	0.0051	−17.28	0	2.56	
UIL CN	0.16221	0.0051	31.79	0	2.56	
UIL US	−0.14344	0.0051	−28.11	0	2.56	
UIL DE	−0.04373	0.0051	−8.57	0	2.56	
UIL KR	0.15453	0.0051	30.29	0	2.56	
Stage * Country						
1 CN	−0.06253	0.00442	−14.15	0	2.4	
1 US	0.06716	0.00442	15.2	0	2.4	
1 DE	0.07085	0.00442	16.03	0	2.4	
1 KR	−0.10244	0.00442	−23.18	0	2.4	
2 CN	0.00552	0.00442	1.25	0.212	2.4	
2 US	0.02315	0.00442	5.24	0	2.4	
2 DE	0.03346	0.00442	7.57	0	2.4	
2 KR	−0.02483	0.00442	−5.62	0	2.4	
3 CN	0.01507	0.00442	3.41	0.001	2.4	
3 US	−0.02079	0.00442	−4.7	0	2.4	
3 DE	−0.03127	0.00442	−7.08	0	2.4	
3 KR	0.03288	0.00442	7.44	0	2.4	
Attributes * Stage * Country						
OPT 1 CN	−0.09788	0.00884	−11.08	0	3.84	
OPT 1 US	0.10102	0.00884	11.43	0	3.84	
OPT 1 DE	0.01868	0.00884	2.11	0.035	3.84	
OPT 1 KR	−0.02242	0.00884	−2.54	0.011	3.84	

Table 4 (*continued*)

General factorial regression: Percentage versus Attributes, Stage, Country

Analysis of variance

Source		DF	Adj SS	Adj MS	F-value	*P*-value
OPT 2 CN	−0.03481	0.00884	−3.94	0	3.84	
OPT 2 US	0.07224	0.00884	8.18	0	3.84	
OPT 2 DE	0.03756	0.00884	4.25	0	3.84	
OPT 2 KR	−0.06404	0.00884	−7.25	0	3.84	
OPT 3 CN	0.02871	0.00884	3.25	0.001	3.84	
OPT 3 US	0.00042	0.00884	0.05	0.962	3.84	
OPT 3 DE	−0.02799	0.00884	−3.17	0.002	3.84	
OPT 3 KR	−0.00176	0.00884	−0.2	0.842	3.84	
GI 1 CN	0.07145	0.00884	8.08	0	3.84	
GI 1 US	−0.03319	0.00884	−3.76	0	3.84	
GI 1 DE	−0.0054	0.00884	−0.61	0.541	3.84	
GI 1 KR	0.00704	0.00884	0.8	0.426	3.84	
GI 2 CN	0.00712	0.00884	0.81	0.421	3.84	
GI 2 US	−0.03457	0.00884	−3.91	0	3.84	
GI 2 DE	0.00358	0.00884	0.41	0.685	3.84	
GI 2 KR	0.02516	0.00884	2.85	0.004	3.84	
GI 3 CN	−0.021	0.00884	−2.38	0.018	3.84	
GI 3 US	−0.02169	0.00884	−2.45	0.014	3.84	
GI 3 DE	0.02266	0.00884	2.56	0.01	3.84	
GI 3 KR	0.00391	0.00884	0.44	0.658	3.84	
IKP 1 CN	−0.16209	0.00884	−18.34	0	3.84	
IKP 1 US	0.05	0.00884	5.66	0	3.84	
IKP 1 DE	0.08516	0.00884	9.64	0	3.84	
IKP 1 KR	−0.07103	0.00884	−8.04	0	3.84	
IKP 2 CN	0.06714	0.00884	7.6	0	3.84	
IKP 2 US	−0.04197	0.00884	−4.75	0	3.84	
IKP 2 DE	0.00839	0.00884	0.95	0.343	3.84	
IKP 2 KR	−0.06292	0.00884	−7.12	0	3.84	
IKP 3 CN	0.08748	0.00884	9.9	0	3.84	
IKP 3 US	−0.0403	0.00884	−4.56	0	3.84	
IKP 3 DE	−0.04336	0.00884	−4.91	0	3.84	
IKP 3 KR	0.03463	0.00884	3.92	0	3.84	
UIL 1 CN	0.07743	0.00884	8.76	0	3.84	
UIL 1 US	−0.08208	0.00884	−9.29	0	3.84	
UIL 1 DE	−0.08102	0.00884	−9.17	0	3.84	
UIL 1 KR	0.10713	0.00884	12.12	0	3.84	
UIL 2 CN	−0.00684	0.00884	−0.77	0.439	3.84	
UIL 2 US	−0.0071	0.00884	−0.8	0.422	3.84	
UIL 2 DE	−0.01704	0.00884	−1.93	0.054	3.84	
UIL 2 KR	0.02348	0.00884	2.66	0.008	3.84	
UIL 3 CN	−0.03569	0.00884	−4.04	0	3.84	
UIL 3 US	0.0305	0.00884	3.45	0.001	3.84	
UIL 3 DE	0.05593	0.00884	6.33	0	3.84	
UIL 3 KR	−0.04037	0.00884	−4.57	0	3.84	

Notes: stage 1 means the time period of before 1985, stage 2 means the time period of 1986–2000, stage 3 means the time period of 2001–2010, and stage 4 means the time period of after 2011.

with a *P*-value of 0.212. The factorial design analysis results are stated in Table 4.

Fig. 4 illustrates similar main effects on innovation from assessing attribute, time period, and country, regardless of the indicator for innovation that the authors use. China and South Korea have large gaps with the United States and Japan in innovation, and Germany has large gaps with the United States and Japan for HighValue, but smaller gaps for Percentage. The innovation of globalization intentions and international knowledge position is more easily achieved than for university-industry linkages and the ownership of platform technology. Although the time periods differ, the innovation capability increases over time, and especially from the periods of 1986–2000 to 2001–2010. The number of valuable patents in the third 10-year stage is much larger than in the second 15-year stage.

4.3.2. Innovation gap changes across countries over time

The authors utilize a *Z*-score normalization to normalize the outputs of different countries' innovation, including high-quality patent counts (HighValue) and the percentage of high-quality patents (Percentage). The data after normalization follows a normal distribution, with a mean of zero and standard deviation of one. The transformation function is

$$y^* = \frac{y - \mu}{\sigma},$$

where y^* is the normalized data, y is the initial data, μ is the sample data's mean, and σ is the sample data's standard deviation. The authors then plot interactions to assess the attribute, time period, and country for normalized high-quality patent counts, as well as normalized percentages of high-quality patents.

Fig. 5 indicates the interactions from assessing attribute and country, and the interactions of time period and country on different assessed attributes, for normalized high-quality patent counts, respectively.

As observed in the interaction plot of Assessing Attribute ∗ Country in Fig. 5, China has a significant gap with Japan on globalization intention (GI) and cross-disciplinary technology development (CTD), as the gaps for these two attributes are greater than one sigma. China does not have a significant gap with other countries for university-industry linkage (UIL) compared to the other attributes, and the five countries'

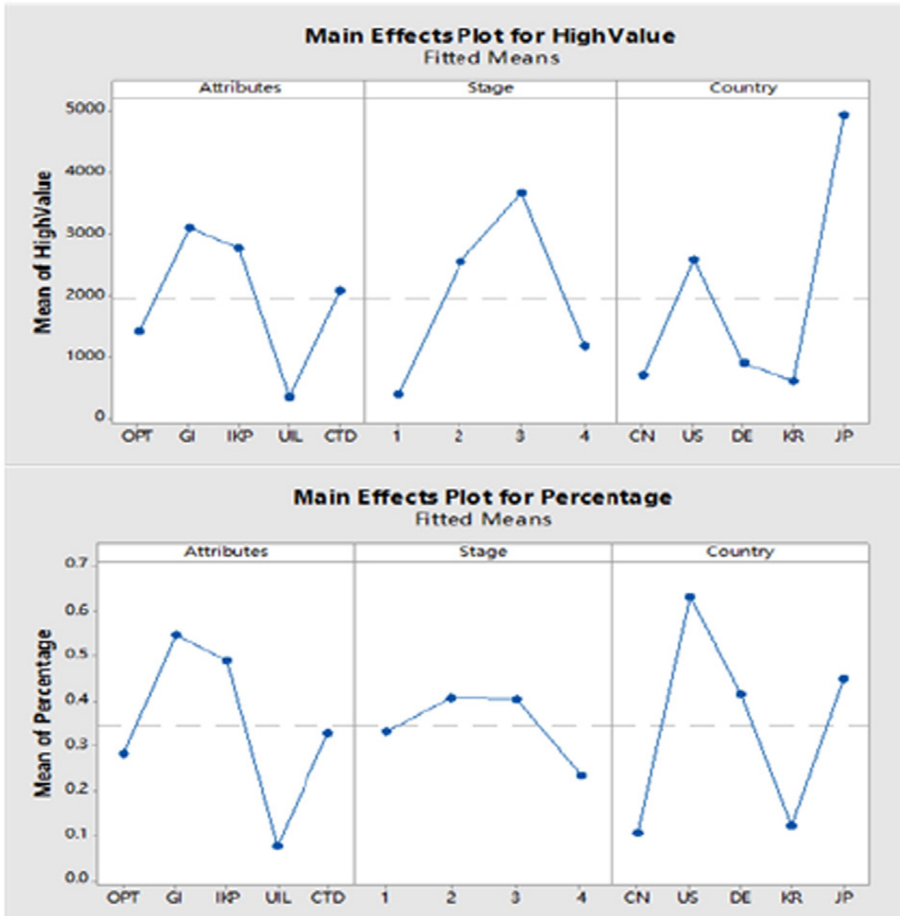

Fig. 4. Main effects on innovation for assessing attribute, time period, and country. (Upper: HighValue, indicating innovation; lower: percentage, indicating innovation).

UIL levels are not as high as the other attributes. The gaps between China and other countries in ownership of platform technologies (OPT) and international knowledge position (IKP) are approximately equal to or less than one sigma, and it can be inferred that these gaps are controlled.

The interaction plots of Time Period ∗ Country in Fig. 5 indicate that the gaps between China and other countries for OPT and IKP are narrowed from the period of 1986–2000 to 2001–2010. The data for the period after 2011 is significantly lower than the other time periods because of the shorter time period length and the delay of data entered into TI's database. China's performances in GI, UIL, and CTD do not significantly change over time, while Japan and the United States improved in these attributes from the periods of 1986–2000 to 2001–2010. The gaps between China and developed countries for GI, UIL, and CTD actually increase over time, as the gaps between China and Japan for GI and CTD are over three sigma, and the gap between China and the United States for UIL has increased to three sigma in the period of 2001–2010.

Fig. 6 indicates the interaction for assessing attribute and country, and the interactions of time period and country on different assessed attributes, respectively, for normalized percentages of high-quality patents in all related patents in the country. All patents cost resources to develop and preserve, and the percentage of high-quality patents among all related patents can present an effective innovation ratio.

As observed in the interaction plot of Assessing Attribute ∗ Country in Fig. 6, China has a significant gap with the United States in globalization intention (GI), and the gap in this attribute measures approximately three sigma. The gap between China and the United States for the ownership of platform technologies (OPT) and the gap between China and Japan for cross-disciplinary technology development (CTD) measure approximately two sigma. The gaps in GI, OPT and CTD between China and the United States or Japan are significant. China performs better on international knowledge position (IKP) than on the other attributes, which is on an average level, while the gap between China and the United States is still significantly larger than one sigma. Compared with the other attributes, China does not have a significant gap with other countries for university-industry linkage (UIL), and the UIL levels for the five countries are lower than average for the five assessed attributes.

As demonstrated in the interaction plots of Time Period ∗ Country in Fig. 6, the gap between China and other countries for OPT has narrowed over time, and the gap between China and the United States for IKP has narrowed from the period prior to 1985 to the period of 1986–2000, and currently remain at similar widths. China's performances for GI, UIL, and CTD are approximately one sigma lower than the attribute's average level, and have not significantly changed over time. The other countries also have not experienced significant changes in the performances of GI and CTD, and the gaps between China and the best country for GI and CTD are approximately two sigma. The United States' performance for UIL improves over time, with the exception of a gentle decline from the period of 2001–2010 to the period after 2011. Further, the gap between China and the United States for UIL measured nearly three sigma from the period prior to 1985 to the period of 2001–2010. Additionally, South Korea performs well for CTD another catching-up country in the analysis, and the gap to the United States or Japan is only one sigma.

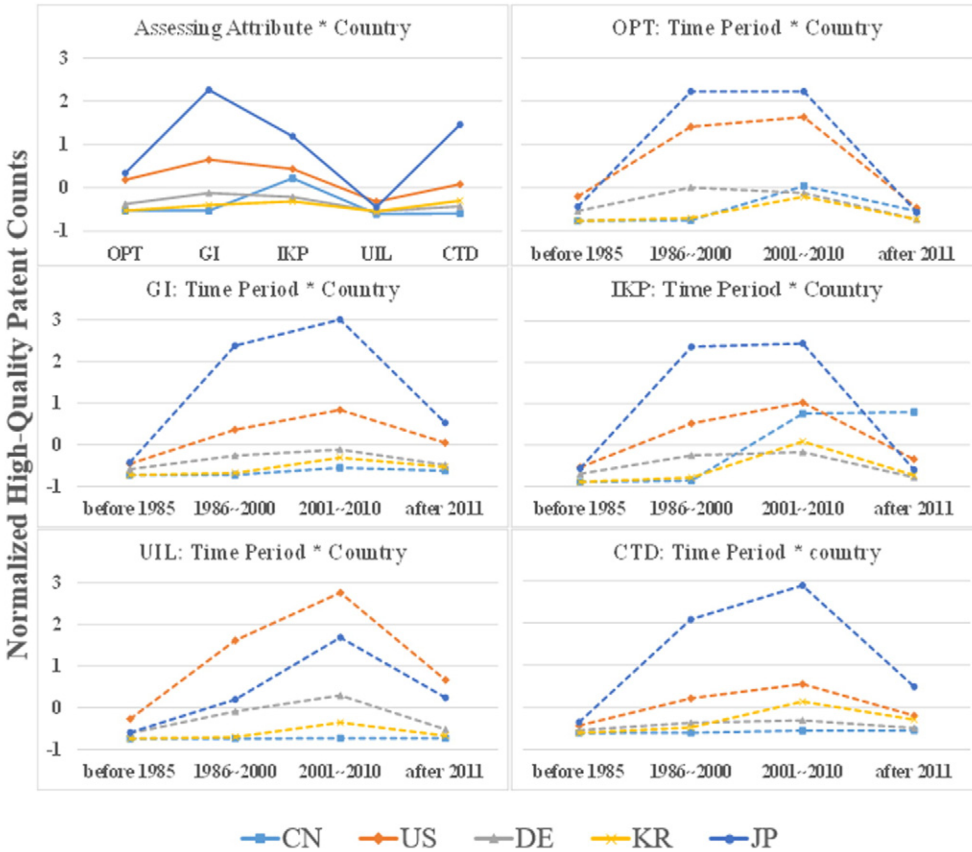

Fig. 5. Interaction plots for high-quality patent counts.

4.4. Validation of high-quality patent counts based on SVMs

Several types of patent indicators can estimate patent value (de Rassenfosse et al., 2013), such as the quantity of the patents granted by the USPTO, patent applications filed at the EPO, triadic patent families, and patent applications with high forward citations. The number of patents granted by the USPTO has been accessible to researchers for some time, and is extensively used for international comparisons (Merton, 1935; Schmookler, 1954; Soete and Wyatt, 1983). The EPO is a regional office in the European patent system, and its count is not biased towards a single country. Statistics on the EPO's patent filings are often assumed as less biased than those at the USPTO (de Rassenfosse et al., 2013). The quantity of triadic patent families is a statistic indicator of patent families, as developed by the Organization for Economic Co-operation and Development (2009). According to the OECD's definition, the triadic patent family is a set of patent applications that have been filed with both the EPO and JPO, and have been granted by the USPTO, and that share one or more priority applications. The high-forward citation criteria is another important indicator of high-value patents (Guan and Gao, 2009; Harhoff et al., 2003; Liu and Zhi, 2010).

Table 5 demonstrates that the count of high-quality patents from the SVM-based classifier significantly correlates with at least one of the traditional indicators. The United States is the origin of robotics, and a country well-known for both original technological developments and the integration of production and research. Thus, the number of patents granted by the USPTO correlates with the number of high-quality patents for ownership of platform technologies (OPT) and university-industry linkages (UIL). Most application and industrialization technology innovations must refer to and cite platform technologies. Therefore, the quantity of patents with high forward citations correlates with the OPTs' high-quality patent counts. Counting patent applications filed at the EPO, the number of triadic patent families is less home-biased, and the patents covered always have medium to high value (de Rassenfosse et al., 2013). Logically, these two indicators significantly correlate with the number of high-quality patents for every assessed attribute.

5. Discussion and conclusions

This research empirically analyzes the industrial robot innovation gap between China and developed countries (the United States, Japan, and Germany). This demonstrates that a support vector machine (SVM) based classifier is reliable in choosing high-quality patents, with high classification accuracy in every assessed attribute. Further, high-quality patent counts are valid to assess innovation, based on significant correlations with traditional innovation indicators.

As the expert opinions in Section 3 reveal, the United States and Japan have solid foundations and the systematized knowledge systems for industrial robotics innovation. This research's method provides similar results in that the United States and Japan are significantly developed countries, and lead industrial robotics innovation by a significant margin, compared to China and South Korea. While Germany is a well-known, industrially developed country, the government does not focus on industrial robotics development as much as Japan. Thus, Germany does not perform as well as Japan and the United States in industrial robotics innovation. However, Germany's performance is still better than newly industrialized China and South Korea's, and especially regarding the effective innovation ratio.

Section 4 notes that the innovation gaps between China and developed countries on the ownership of platform technologies (OPT) and international knowledge position (IKP) have narrowed since the beginning of the 21st century. Innovation in China has improved to a certain extent with comprehensive economic increases. As the literature reviews in Section 3 illustrate, China began its organized, systemic

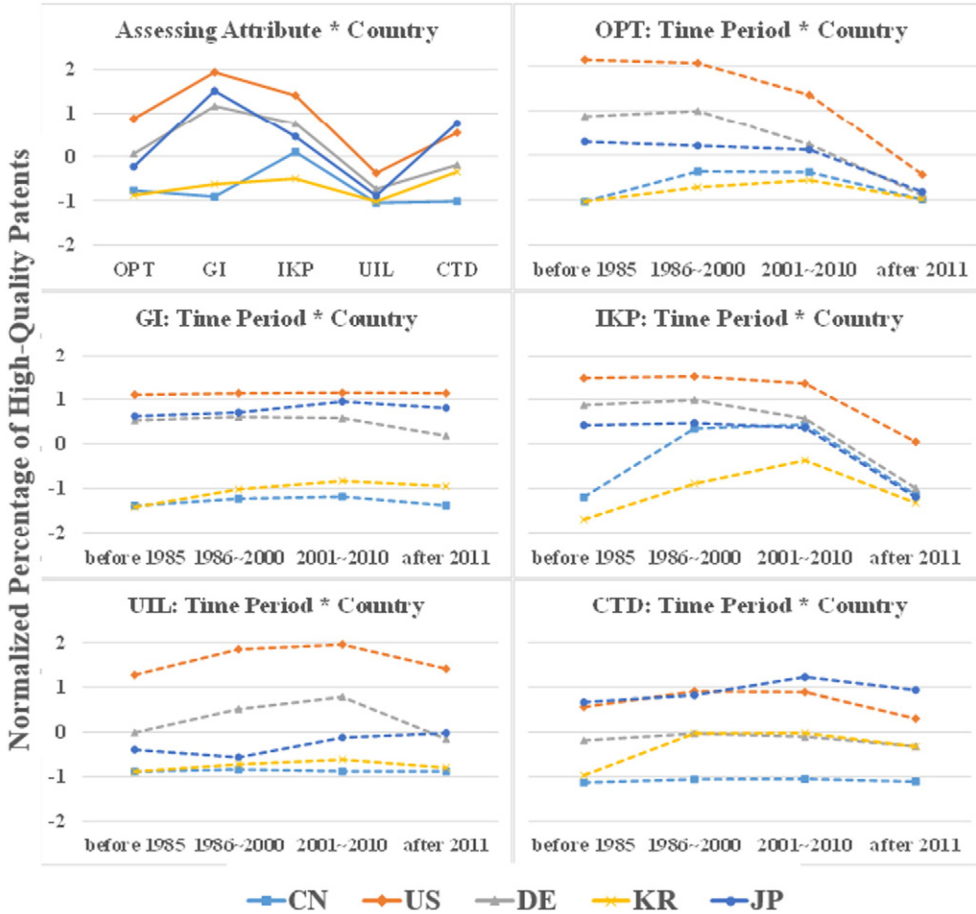

Fig. 6. Interaction plots for percentages of high-quality patents.

industrial robotics research in 1986, and recognized the industrial robotics industry's importance in the early 21st century; the industrialization of China's industrial robotics manufacturing also began at this time. Chinese scholars and the central government have discovered that a lack of core, critical generic technologies has created a bottleneck in industrial robotics development, and significant research efforts, including money and talent, is invested in both core and critical technologies. Therefore, the innovation gaps between China and developed countries have narrowed, to a certain extent.

Moreover, the empirical analysis' results indicate that a substantial innovation gap still exists between China and developed countries regarding globalization intention (GI). China has become the largest global industrial robotics market, and logically, Chinese organizations do not have strong globalization intentions, as reflected in the country's patent applications. A country's GI is an important attribute to assess innovation, as this presents the organization's confidence in participating in international competition. This attribute indicates the national and

Table 5
Correlation coefficients.

	OPT	GI	IKP	UIL	CTD
USPTO	0.540*	0.349	0.334	0.884**	0.282
EPO	0.773**	0.717**	0.604**	0.605**	0.664**
Triadic	0.859**	0.987**	0.839**	0.587**	0.981**
High forward citations	0.539*	0.237	0.280	0.633**	0.189

Notes: data for the four Time Periods * Five Countries, or the same as in Section 4. A patent with more than 50 forward citations is defined as a patent with high forward citations.
* Coefficient is statistically significant at the 5% level.
** Coefficient is statistically significant at the 1% level.

international competitiveness of innovation, which cannot be ignored to assess innovation on a national scale.

The innovation gaps between China and developed countries for university-industry linkage (UIL) and cross-disciplinary technology development (CTD) become more serious with the developed countries' improvement over time. Investors have found that a gap exists between innovation and its commercialization, or the “Death Valley.” American scholars of public administration, business administration, risk investment, and technology have recognized the scale of this problem, and have conducted many research studies and practices to promote the cooperation of universities, research institutes, and industry. The United States has had many successful experiences in this cooperation, and its industrial robotics innovation in UIL is far superior to China's. As aforementioned, Japan's development of industrial robotics began with production, which significantly differs from China's; further, the innovation commercialization problem is less serious in Japan than in China. Innovation aims to generate commercial profits, and the substantial UIL innovation gap should compel China to focus on the cooperation of its universities, research institutes, and industry. Additionally, industrial robotics technologies are multidisciplinary, involving mechanical, electrical, optical, and computer engineering, as well as application scenarios. The weak technology foundation and a lack of successful interdisciplinary collaboration experiences cause primitive innovation for CTD compared with the United States, Japan, and Germany.

In this study, the authors conducted a method to assess the innovation gap between catching-up and developed countries for emerging industries based on data-mining. The authors utilized support vector machines algorithm to obtain high-quality patents to analyze the national innovation gaps in the industrial robot sector, in terms of OPT, GI, IKP, UIL, and CTD. It provides reliable and valid innovation assessment results, and shows that China has significant innovation gaps with the United States and Japan. The innovation gaps tend to increase for GI, UIL, and CTD. Our main conclusions are as follows.

First, this comprehensive, systematic method for innovation gap assessment can cover shortages in traditional single indicators' serious preferences, as well as provide a fixed-weights assignment of traditional multi-attribute evaluation methods. The method involves experts' knowledge to choose sets of training examples and assess their attributes, and utilizes a proper algorithm-based machine learning classifier to categorize high-quality data regarding the assessing attributes. Further, the high-quality patent counts in this research represent innovation, and the proper algorithms are SVMs, based on the literature review. The assessed attributes for emerging industries are the OPT, GI, IKP, UIL, and CTD, which derive from the previous innovation evaluation research. This research empirically analyzes the industrial robot innovation gap between China and developed countries (the United States, Japan, and Germany). This demonstrates that an SVM-based classifier is reliable in choosing high-quality patents, with high classification accuracy in every assessed attribute. Further, high-quality patent counts are valid to assess innovation, based on significant correlations with traditional innovation indicators.

In addition, the empirical analysis indicates that China has a significant innovation gap with the United States and Japan regarding GI, UIL, and CTD; further, these innovation gaps have increasing trends for these attributes. Innovation gaps exist between China and the United States, Japan, and Germany for OPT and IKP, and the gaps have narrowed over time. Investments of money and technical talents in industrial robotics have generated certain innovative achievements. However, money and technical talents cannot solve every problem, such as improving cooperation consciousness and mechanisms, and increasing confidence in competing internationally. China, as a catching-up country, requires patience to solve these problems, must further strengthen its technology foundation, and establish positive cooperation habits and mechanisms.

Based on the analysis in the industrial robot sector, China has narrowed innovation gaps on OPT and IKP, which provides their chance of leapfrogging to the R&D of new technologies, while has increasing innovation gaps compared with developed countries on GI, UIL, and CTD, which limits the chance of leapfrogging to diffuse and industrialize the new technologies. It suggests China's policy to focus on the cooperation experiences accumulation, and also technology diffusion and industrialization. As the assessed attributes in the research do not have special evaluation targets except for the emerging industry, the innovation gap assessment method has good suitability and scalability for emerging industries besides industrial robotics. This research provides a comprehensive evaluation method of national innovation gaps avoiding biases of traditional patent analysis methods, which is significantly advantageous in its batch processing of massive data.

There are limitations to the research. First, patent analysis methods must take care to reduce the data bias in future research. The analysis only based on patent database may cause false results due to data bias, so future research may consider using multi-source heterogeneous data. Second, this research utilizes an effective machine learning algorithm based on a previous research, while there are multiple machine learning algorithms, which may reach a better result to assess innovation gaps between countries. Third, the research chooses industrial robotics as the empirical analysis target, which is only one special case of emerging industries. In the future research, we should consider more cases of emerging industries to prove the effectiveness of the method, and verify the most effective machine learning algorithm in the method. Furthermore, we may integrate more sources of data into the method to make the assessment more objective and just.

Acknowledgement

This research is supported by the National Natural Science Foundation of China (Grant Numbers: 91646102, L16240452, L1524015, 71203117), and the MOE (Ministry of Education in China) Project of Humanities and Social Sciences (Grant Number: 16JDGC011). This research is also supported in part by the Volvo Group in a research project of the Research Center for Green Economy and Sustainable Development, Tsinghua University (20153000181).

References

Acs, Z.J., Anselin, L., Varga, A., 2002. Patents and innovation counts as measures of regional production of new knowledge. Res. Policy 31:1069–1085. http://dx.doi.org/10.1016/S0048-7333(01)00184-6.

Anderson, E., Naughton, T.M., Cowhey, P., Xue, L., Chen, L., Wang, G., 2013. Measuring the U.S.-China innovation gap: initial findings of the UCSD-Tsinghua Innovation Metrics Survey Project. Study of Innovation & Technology in China: Research Briefs December 2013 (available at SSRN: https://escholarship.org/uc/item/89m2s993).

Archibugi, D., Cesaratto, S., Sirilli, G., 1991. Sources of innovative activities and industrial organization in Italy. Res. Policy 20 (4):299–313. http://dx.doi.org/10.1016/0048-7333(91)90091-4.

Ávila-Robinson, A., Miyazaki, K., 2013. Dynamics of scientific knowledge bases as proxies for discerning technological emergence — the case of MEMS/NEMS technologies. Technol. Forecast. Soc. Chang. 80 (6):1071–1084. http://dx.doi.org/10.1016/j.techfore.2012.07.012.

Beck-Broichsitter, M., Schmehl, T., Gessler, T., Seeger, W., Kissel, T., 2012. Development of a biodegradable nanoparticle platform for sildenafil: formulation optimization by factorial design analysis combined with application of charge-modified branched polyesters. J. Control. Release 157 (3):469–477. http://dx.doi.org/10.1016/j.jconrel.2011.09.058.

Bekkers, R., Martinelli, A., 2012. Knowledge positions in high-tech markets: trajectories, standards, strategies and true innovators. Technol. Forecast. Soc. Chang. 79 (7): 1192–1216. http://dx.doi.org/10.1016/j.techfore.2012.01.009.

Bettencourt, L.M.A., Kaiser, D.I., Kaur, J., 2009. Scientific discovery and topological transitions in collaboration networks. J. Informet. 3 (3):210–221. http://dx.doi.org/10.1016/j.joi.2009.03.001.

Caillaud, B., Duchêne, A., 2011. Patent office and innovation policy: nobody's perfect. Int. J. Ind. Organ. 29 (2):242–252. http://dx.doi.org/10.1016/j.ijindorg.2010.06.002.

Cao, X., Xie, C., 2008. History of robotics in China (in Chinese). Robot Tech. Appl. 5, 44–46.

Carlsson, B., 1984. The development and use of machine tools in historical perspective. J. Econ. Behav. Organ. 5 (1):91–114. http://dx.doi.org/10.1016/0167-2681(84)90028-3.

Castellacci, F., Natera, J.M., 2016. Innovation, absorptive capacity and growth heterogeneity: development paths in Latin America 1970–2010. Struct. Chang. Econ. Dyn. 37: 27–42. http://dx.doi.org/10.1016/j.strueco.2015.11.002.

Choi, S.B., Lee, S.H., Williams, C., 2011. Ownership and firm innovation in a transition economy: evidence from China. Res. Policy 40:441–452. http://dx.doi.org/10.1016/j.respol.2011.01.004.

Choung, J., Hwang, H., Song, W., 2014. Transitions of innovation activities in latecomer countries: an exploratory case study of South Korea. World Dev. 54 (1):156–167. http://dx.doi.org/10.1016/j.worlddev.2013.07.013.

Cohen, W.M., Goto, A., Nagata, A., Nelson, R.R., Walsh, J.P., 2002. R&D spillovers, patents and the incentives to innovate in Japan and the United States. Res. Policy 31 (8–9): 1349–1367. http://dx.doi.org/10.1016/S0048-7333(02)00068-9.

Corrocher, N., Malerba, F., Montobbio, F., 2003. How do new technologies emerge? A patent-based analysis of ICT-related new industrial activities. Innov. Manag. Policy Pract. 5 (2/3), 234–256.

Cortes, C., Vapnik, V., 1995. Support-vector networks. Mach. Learn. 20 (3):273–297. http://dx.doi.org/10.1007/BF00994018.

Cowan, R., Jonard, N., 1999. Network structure and the diffusion of knowledge. J. Econ. Dyn. Control 28 (8):1557–1575. http://dx.doi.org/10.1016/j.jedc.2003.04.002.

Cox, T.H., Blake, S., 1991. Managing cultural diversity: implications for organizational competitiveness. Executive 5 (3), 45–56.

Ernst, H., 2001. Patent applications and subsequent changes of performance: evidence from time-series cross-section analyses on the firm level. Res. Policy 30 (1): 143–157. http://dx.doi.org/10.1016/S0048-7333(99)00098-0.

Ernst, H., 2003. Patent information for strategic technology management. World Patent Inf. 25 (3):233–242. http://dx.doi.org/10.1016/S0172-2190(03)00077-2.

Ernst, D., 2016. From catching up to forging ahead? China's new role in the semiconductor industry (May 2016). Solid state technology May 2016. available at SSRN: http://ssrn.com/abstract=2769383.

Ernst, D., Kim, L., 2002. Global production networks, knowledge diffusion, and local capability formation. Res. Policy 31 (8–9):1417–1429. http://dx.doi.org/10.1016/S0048-7333(02)00072-0.

Ernst, H., Omland, N., 2011. The patent asset index—a new approach to benchmark patent portfolios. World Patent Inf. 33 (1):34–41. http://dx.doi.org/10.1016/j.wpi.2010.08.008.

Fan, P., 2006. Catching up through developing innovation capability: evidence from China's telecom-equipment industry. Technovation 26 (3):359–368. http://dx.doi.org/10.1016/j.technovation.2004.10.004.

Forés, B., Camisón, C., 2016. Does incremental and radical innovation performance depend on different types of knowledge accumulation capabilities and organizational size? J. Bus. Res. 69 (2):831–848. http://dx.doi.org/10.1016/j.jbusres.2015.07.006.

Fu, X., 2008. Foreign direct investment: absorptive capacity and regional innovation capabilities: evidence from China. Oxf. Dev. Stud. 36:89–110. http://dx.doi.org/10.1080/13600810701848193.

Fu, X., Yang, Q.G., 2009. Exploring the cross-country gap in patenting: a stochastic frontier approach. Res. Policy 38 (7):1203–1213. http://dx.doi.org/10.1016/j.respol.2009.05.005.

Fu, X., Pietrobelli, C., Soete, L., 2011. The role of foreign technology and indigenous innovation in the emerging economies: technological change and catching-up. World Dev. 39 (7):1204–1212. http://dx.doi.org/10.1016/j.worlddev.2010.05.009.

Gao, P., 2015. Government in the catching-up of technology innovation: case of administrative intervention in China. Technol. Forecast. Soc. Chang. 96:4–14. http://dx.doi.org/10.1016/j.techfore.2015.01.014.

Gibbons, M., 1994. The New Production of Knowledge. Sage, London, Thousand Oaks.

Gosens, J., Lu, Y., 2014. Prospects for global market expansion of China's wind turbine manufacturing industry. Energy Policy 67:301–318. http://dx.doi.org/10.1016/j.enpol.2013.12.055.

Graefe, V., Bischoff, R., 2009. From ancient machines to intelligent robots — A technical evolution. The 9th International Conference on Electronic Measurement & Instruments (ICEMI 2009), 3-418-3-431 http://dx.doi.org/10.1109/ICEMI.2009.5274297.

Grimaldi, M., Cricelli, L., Rogo, F., 2012. A methodology to assess value creation in communities of innovation. J. Intellect. Cap. 13 (3):305–330. http://dx.doi.org/10.1108/14691931211248882.

Gu, Q., Jiang, W., Wang, G.G., 2016. Effects of external and internal sources on innovation performance in Chinese high-tech SMEs: a resource-based perspective. J. Eng. Technol. Manag. 40:76–86. http://dx.doi.org/10.1016/j.jengtecman.2016.04.003.

Guan, J., Chen, K., 2012. Modeling the relative efficiency of national innovation systems. Res. Policy 41:102–115. http://dx.doi.org/10.1016/j.respol.2011.07.001.

Guan, J., Gao, X., 2009. Exploring the h-index at patent level. J. Am. Soc. Inf. Sci. Technol. 60 (1):35–40. http://dx.doi.org/10.1002/asi.20954.

Guan, J., Yam, R.C.M., 2015. Effects of government financial incentives on firms' innovation performance in China: evidences from Beijing in the 1990s. Res. Policy 44 (1): 273–282. http://dx.doi.org/10.1016/j.respol.2014.09.001.

Guan, J., Yam, R.C.M., Mok, C.K., 2005. Collaboration between industry and research institutes/universities on industrial innovation in Beijing, China. Tech. Anal. Strat. Manag. 17 (3):339–353. http://dx.doi.org/10.1080/09537320500211466.

Hadorn, G.H., Biber-Klemm, S., Grossenbacher-Mansuy, W., Hoffmann-Riem, H., Joye, D., Pohl, C., Wiesmann, U., Zemp, E., 2007. The emergence of transdisciplinarity as a form of research. Handbook of Transdisciplinary Research:pp. 19–39 http://dx.doi.org/10.1007/978-1-4020-6699-3_2.

Harhoff, D., Hoisl, K., 2007. Institutionalized incentives for ingenuity—patent value and the German Employees' Inventions Act. Res. Policy 36 (8):1143–1162. http://dx.doi.org/10.1016/j.respol.2007.07.010.

Harhoff, D., Scherer, F.M., Vopel, K., 2003. Citations, family size, opposition and the value of patent rights. Res. Policy 32 (8):1343–1363. http://dx.doi.org/10.1016/S0048-7333(02)00124-5.

Harrington, P., 2012. Machine Learning in Action. Manning Publications Co., NY.

Herring, C., 2009. Does diversity pay?: race, gender, and the business case for diversity. Am. Sociol. Rev. 74 (2):208–224. http://dx.doi.org/10.1177/000312240907400203.

Hitachi, L., 2008. Master Slave Manipulator System: German, EP20080001129 (2008-09-24).

Hobday, M., 1998. Latecomer catch-up strategies in electronics: Samsung of Korea and ACER of Taiwan. Asia Pac. Bus. Rev. 4 (2–3):48–83. http://dx.doi.org/10.1080/13602389812331288364.

Hong, W., Su, Y., 2013. The effect of institutional proximity in non-local university–industry collaborations: an analysis based on Chinese patent data. Res. Policy 42:454–464. http://dx.doi.org/10.1016/j.respol.2012.05.012.

Hu, M.C., Mathews, J.A., 2008. China's national innovative capacity. Res. Policy 37 (9): 1465–1479. http://dx.doi.org/10.1016/j.respol.2008.07.003.

Hung, S.C., Chu, Y.Y., 2006. Stimulating new industries from emerging technologies: challenges for the public sector. Technovation 26 (1):104–110. http://dx.doi.org/10.1016/j.technovation.2004.07.018.

International Federation of Robotics (IFR), 2011. Industrial breakthrough with robots 2011: the most successful year for industrial robots since 1961 [EB/OL]. http://www.ifr.oro/news/ifr-press-release/industrial-breakthroughwith-robots-381/.

International Federation of Robotics (IFR), 2012. History of industrial robots online brochure by IFR2012 [EB/OL]. http://www.ifr.org/news/ifr-press-release/50-years-industrial-robots-410/.

International Federation of Robotics (IFR), 2013a. Service robots [EB/OL]. http://ifr.org/service-robots/.

International Federation of Robotics (IFR), 2013b. Industrial robotics standardization [EB/OL]. http://www.ifr.org/news/ifr-press-release/iso-robotics-standardisation-35/.

International Federation of Robotics (IFR), 2013c. Industrial robot as defined by ISO 8373 [EB/OL]. http://www.ifr.org/industrial-robots/.

Jaffe, A.B., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Q. J. Econ. 108:577–598. http://dx.doi.org/10.2307/2118401.

Jehn, K.A., Neale, M.A., 1999. Why differences make a difference: a field study of diversity, conflict and performance in workgroups. Adm. Sci. Q. 44 (44):741–763. http://dx.doi.org/10.2307/2667054.

Joachims, T., 1998. Text categorization with support vector machines: learning with many relevant features. Proceedings of European Conference on Machine Learning 1398, pp. 137–142.

Jone, M., 2013. A brief history of awesome robots [EB/OL]. http://www.motherjones.coc/media/2013/05/robots-modern-unimate-watson-roomba-timeline.

Kilduff, M., Mehra, A., 2000. Top management-team diversity and firm performance: examining the role of cognitions. Organ. Sci. 11 (1), 21–34.

Kim, L., 1980. Stages of development of industrial technology in a developing country: a model. Res. Policy 9 (3):254–277. http://dx.doi.org/10.1016/0048-7333(80)90003-7.

Kumaresan, N., Miyazaki, K., 1999. An integrated network approach to systems of innovation — the case of robotics in Japan. Res. Policy 28 (1999):563–585. http://dx.doi.org/10.1016/S0048-7333(98)00128-0.

Li, J., Strange, R., Ning, L., Sutherland, D., 2016. Outward foreign direct investment and domestic innovation performance: evidence from China. Int. Bus. Rev. 25 (5): 1010–1019. http://dx.doi.org/10.1016/j.ibusrev.2016.01.008.

Liefner, I., 2003. Funding, resources and performance in higher education systems. High. Educ. 46:469–489. http://dx.doi.org/10.1023/A:1027381906977.

Liu, X., Zhi, T., 2010. China is catching up in science and innovation: the experience of the Chinese Academy of Sciences. Sci. Public Policy 37 (5):331–342. http://dx.doi.org/10.3152/030234210X501162.

Lyall, C., Tait, J., Meagher, L., Bruce, A., Marsden, W., 2011. A short guide to evaluating interdisciplinary research. The Institute for the Study of Science Technology and Innovation Briefing Note (No. 9) March 2011 (www.tinyurl.com/idwiki).

Macdonald, R.R., 2011. The importance of being OSCAR or Balance and the analysis of factorial designs. Br. J. Math. Stat. Psychol. 44 (1):207–220. http://dx.doi.org/10.1111/j.2044-8317.1991.tb00956.x.

Mellor, R., Hyland, P.W., 2005. Manufacturing management programs: are developing economies bridging the strategic gap? Technovation 25 (8):857–863. http://dx.doi.org/10.1016/j.technovation.2004.01.009.

Merton, R., 1935. Fluctuations in the rate of industrial invention. Q. J. Econ. 49 (3): 454–474. http://dx.doi.org/10.2307/1883863.

Meyer, M., Libaers, D., Park, J.H., 2011. The emergence of novel science-related fields: regional or technological patterns? Exploration and exploitation in United Kingdom nanotechnology. Reg. Stud. 45 (7):935–959. http://dx.doi.org/10.1080/00343401003792468.

Nemet, G.F., 2009. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. Res. Policy 38 (5):700–709. http://dx.doi.org/10.1016/j.respol.2009.01.004.

Onsi, M., 1975. Simulation of the economic factors affecting organizational slack: a factorial design. Decis. Sci. 6 (1):78–91. http://dx.doi.org/10.1111/j.1540-5915.1975.tb00999.x.

Organization for Economic Co-operation and Development (OECD), 2009. OECD Patent Statistics Manual (Paris).

Oura, M.M., Zilber, S.N., Lopes, E.L., 2016. Innovation capacity, international experience and export performance of SMEs in Brazil. Int. Bus. Rev. 25 (4):921–932. http://dx.doi.org/10.1016/j.ibusrev.2015.12.002.

OuYang, K., Weng, C.S., 2011. A new comprehensive patent analysis approach for new product design in mechanical engineering. Tech. Forcasting Soc. Chang. 78 (7): 1183–1199. http://dx.doi.org/10.1016/j.techfore.2011.02.012.

Pavitt, K., Walker, W., 1976. Government policies towards industrial innovation: a review. Res. Policy 5 (1):11–97. http://dx.doi.org/10.1016/0048-7333(76)90017-2.

Perez, C., 2010. Technological dynamism and social inclusion in Latin America: a resource-based production development strategy. CEPAL Rev. 100, 121–141.

Pianta, M., Archibugi, D., 1996. Innovation surveys and patents as technology indicators: the state of arts. Innovation, Patents and Technological Activities in Industrial Countries: The Analysis of Patent Data, OECD.

Porter, A.L., Detampel, M.J., 1995. Technology opportunities analysis. Tech. Forcasting Soc. Chang. 49 (49):237–255. http://dx.doi.org/10.1016/0040-1625(95)00022-3.

de Rassenfosse, G., Dernis, H., Guellec, D., Picci, L., de la Potterie, B.P., 2013. The worldwide count of priority patents: a new indicator of inventive activity. Res. Policy 42: 720–737. http://dx.doi.org/10.1016/j.respol.2012.11.002.

Robotworx, 2013. History of industrial robots [EB/OL]. http://www.robots.com/education/industrial-history.

Rogo, F., Cricelli, L., Grimaldi, M., 2014. Assessing the performance of open innovation practices: a case study of a community of innovation. Technol. Soc. 38:60–80. http://dx.doi.org/10.1016/j.techsoc.2014.02.006.

Rotolo, D., Hicks, D., Martin, B.R., 2015. What is an emerging technology? Res. Policy 44: 1827–1843. http://dx.doi.org/10.1016/j.respol.2015.06.006.

Schilling, M.A., Phelps, C.C., 2007. Interfirm collaboration networks: the impact of large-scale network structure on firm innovation. Manag. Sci. 53 (7), 1113–1126.

Schmookler, J., 1954. The level of inventive activity. Rev. Econ. Stat. 36 (2):183–190. http://dx.doi.org/10.2307/1924669.

Schumpeter, J.A., 1942. Cost and demand functions of the individual firm. Am. Econ. Rev. 32 (1):349–350 (http://www.jstor.org/stable/1815132).

Shao, B.B.M., Lin, W.T., 2016. Assessing output performance of information technology service industries: productivity, innovation and catch-up. Int. J. Prod. Econ. 172: 43–53. http://dx.doi.org/10.1016/j.ijpe.2015.10.026.

Soete, L., Wyatt, S., 1983. The use of foreign patenting as an internationally comparable science and technology output indicator. Scientometrics 5 (1):31–54. http://dx.doi.org/10.1007/BF02097176.

Song, X., Yao, Z., 2015. Three barriers to realize leap-forward development of industrial robots in China (in Chinese). Robot Ind. 1 (1), 40–45.

Srinivasan, R., 2008. Sources, characteristics and effects of emerging technologies: research opportunities in innovation. Ind. Mark. Manag. 37 (6):633–640. http://dx.doi.org/10.1016/j.indmarman.2007.12.003.

Sun, Y., Luo, A., 2012. Development institute of industrial robots (in Chinese). Sci. Tech. Eng. 12 (12), 2912–2918.

Tong, X., Frame, J.D., 1994. Measuring national technological performance with patent claims data. Res. Policy 23 (2):133–141. http://dx.doi.org/10.1016/0048-7333(94)90050-7.

Torgny, B., 2007. Present and future robot control development — an industrial perspective. Annu. Rev. Control. 31:69–79. http://dx.doi.org/10.1016/j.arcontrol.2002.01.002.

Usai, S., 2011. The geography of inventive activity in OECD regions. Reg. Stud. 45: 711–731. http://dx.doi.org/10.1080/00343401003792492.

Uzzi, B., Spiro, J., 2005. Collaboration and Creativity: The Small World Problem. Am. J. Sociol. 111 (2):447–504. http://dx.doi.org/10.1086/432782.

Vecchi, A., Brennan, L., 2009. A cultural perspective on innovation in international manufacturing. Res. Int. Bus. Financ. 23 (2):181–192. http://dx.doi.org/10.1016/j.ribaf.2008.03.008.

Venugopalan, S., Rai, V., 2015. Topic based classification and pattern identification in patents. Tech. Forcasting Soc. Chang. 94:236–250. http://dx.doi.org/10.1016/j.techfore.2014.10.006.
Wang, T., 2007. To promote the robotics technology in China (in Chinese). Robot Tech. Appl. 2:17–23. http://dx.doi.org/10.3969/j.issn.1004-6437.2007.02.005.
Wang, C.C., Lin, G.C.S., 2013. Dynamics of innovation in a globalizing China: regional environment, inter-firm relations and firm attributes. J. Econ. Geogr. 13:397–418. http://dx.doi.org/10.1093/jeg/lbs019.
Wang, T., Tao, Y., 2014. Research status and industrialization development strategy of Chinese industrial robot. J. Mech. Eng. 50 (9):1–13. http://dx.doi.org/10.3901/JME.2014.09.001.
Wu, C., Mathews, J.A., 2012. Knowledge flows in the solar photovoltaic industry: insights from patenting by Taiwan, Korea, and China. Res. Policy 41 (3):524–540. http://dx.doi.org/10.1016/j.respol.2011.10.007.
Wu, H., Chen, J., Jiao, H., 2016. Dynamic capabilities as a mediator linking international diversification and innovation performance of firms in an emerging economy. J. Bus. Res. 69 (8):2678–2686. http://dx.doi.org/10.1016/j.jbusres.2015.11.003.
Xu, Y., Yan, J., 2012. New progress in robotics (in Chinese). Integr. Technol. 2012 (1), 8–12.
Zehir, C., Can, E., Karaboga, T., 2015. Linking entrepreneurial orientation to firm performance: the role of differentiation strategy and innovation performance. Procedia. Soc. Behav. Sci. 210:358–367. http://dx.doi.org/10.1016/j.sbspro.2015.11.381.
Zhao, J., 2012. Challenges facing the development of industrial robots (in Chinese). Aeronaut. Manuf. Technol. 2012 (12), 27–29.

Dejing Kong is a lecturer at Beijing University of Posts and Telecommunications (School of Modern Post), and a joint post-doctoral researcher at Tsinghua University (School of Public Policy and Management) and the Chinese Academy of Engineering. Her research interest focuses on innovation policy and advanced manufacturing development strategies.

Yuan Zhou is an associate professor at the School of Public Policy and Management, Tsinghua University, China. His recent research interests include public policy, innovation policy and management. He has published several papers in Science and Public Policy, Technological Forecasting & Social Change, Sustainable Development, Energy for Sustainable Development, International Journal of Technology Management, Innovation: Management Policy & Practice, etc.

Yufei Liu is a PhD candidate at the College of Life Science and Technology, Huazhong University of Science and Technology, China. His research interest focuses on bioinformatics, data mining, and machine learning.

Lan Xue is the Dean and professor at the School of Public Policy and Management, Tsinghua University, China. His recent research interests include public policy, innovation policy, and risk management.