PATENT STRATEGY IN THE DIGITAL TRANSFORMATION ERA

Elona Marku*
University of Cagliari
Viale Fra Ignazio 74 – 09123
Cagliari, Italy

Abstract

The digital transformation and big data paradigms have expanded across many research fields, including both strategy and innovation. Although existing research attempts to keep up with the pace of these phenomena, more in-depth knowledge of how patent big data can help firms and managers in their decision-making process is still needed. Based on patent co-classification analysis, this paper aims to provide two different but complementary patent tools; the first exploits ex-ante patent information whereas the latter integrates it with ex-post details extracted by patent documents. We further investigate the technology positioning and links as well as examine the industry's «excellence» technology structure conceived as the combination of the technology elements that has yielded high-impactful inventions.

Keywords: Innovation, big data, digital transformation, patents, VOSviewer

Introduction

The digital transformation and big data paradigms have expanded across many research fields, including both strategy and innovation (Park, Lee, & Jun, 2016). The great amount of data available is increasingly considered a key factor for gaining a competitive advantage especially in fast-moving markets (Park, Kim, Choi, & Yoon, 2013). In particular, business intelligence and analytics have become essential for firms in their decision-making process, helping the investigation of firms' technology network and positioning within a broader scenario, for instance when focusing on industry level (Breschi, Lissoni, & Malerba, 2003; Yayavaram & Ahuja, 2008; Suominen, Toivanen, & Seppänen, 2017). Indeed, firms continually make decisions of whether investing in core technologies or diversifying their portfolio with novel although risky technologies (Christensen,1997; 2013; Tushman & O'Reilly, 1996), whether growing organically through internal R&D or extending the firm's knowledge boundaries through mergers and acquisitions or alliances (Cassiman et al., 2005; Gilsing et al., 2008). To take the most suitable decision, firms should have a detailed overview of the sector's knowledge network and structure, and attempt to identify potential future technology trends (Engelsman & van Raan, 1994).

Existing innovation studies use patents to extract useful information on firm's inventive activities. More specifically, research can be classified into two different but complementary approaches: content-based approach utilizing the text of abstracts, description of the invention, and claims (Tseng et al., 2011; Yoon, Park, & Coh, 2014), and bibliographic approach via the use of citations, co-citations, applicants, inventors, and patent classification codes (No & Park, 2010). The latter approach represents an effective alternative to the most widespread patent co-citation analysis (Tijssen, 1992; Leydesdorff, 2008; Luan, Liu, & Wang, 2013; Spasser, 1997; Castriotta & Di Guardo, 2015; 2016; Loi, Castriotta, & Di Guardo, 2016). Departing far from extant literature, we map the co-occurrence of the technology classification codes using a novel but validated visualization software, the VOSviewer, that exploits an algorithm for computing similarity measures that allow the overcoming of some of the artifacts produced by the more traditional multidimensional scaling (van Eck et al. 2006; van Eck & Waltman, 2007; Waaijer, van Bochove, & van Eck, 2010; van Eck et al., 2010; Zupic & Čater 2015).

Our enrichment to the existing literature consists in providing two different tools helpful for firms in their decision-making process. On the one hand, we map and visualize an overview of the industry's knowledge structure to identify the technology structure and positioning, while on the other hand, we highlight the «excellence» technology structure conceived as the combination of the technology elements that have yielded inventions with a high technological impact.

In addition, following the latest trend in innovation studies and avoiding the limitations of the International Patent Classification (IPC) system (Luan, 2013), we use the Derwent World Patent Index (DWPI) classification codes (Calcagno, 2008; Luan, Liu, & Wang, 2013; Luan et al., 2014; Marku & Zaitsava, 2018). A specific characteristic of the DWPI system regards the assignment of one or several manual codes to a single patent document, aiming at the coverage of all the relevant aspects of the invention. In this way, we can capture the smallest knowledge elements possessed by the firm. In this paper, we examine the U.S. communications industry as in the last decades it has been characterized by a high technological heterogeneity and dynamism. We analyzed patents granted to firms operating in this industry in the time interval that goes from 1992 to 2011, including more than 120.000 U.S. patents. We then generated two maps to investigate the industry's technology structure as well as to highlight the so-called "excellence" technology structure.

The remainder of the paper is structured as follows. In section 2, we review the literature on patent analysis whereas, in Section 3, we propose two patent tools using a patent co-classification approach and the VOSviewer software. Section 4 includes a description of the main results of the present study. Last, our discussion, conclusion, limitations, and future research are presented in Section 5.

Literature Background

The digital transformation has incredibly fostered what scholars call "big data". The main features of big data are its volume, variety, and velocity (Gartner, 2015; Park et al., 2016). The high-intensity of the patenting activity and the explosive growth of the Internet has led to a dramatic increase in data sources (included patents) for competitive technology intelligence able to identify technology opportunities for firms (Veugelers, Bury, & Viane, 2010). For these reasons, patents can be considered big data. Additionally, the rich information included in patent documents (i.e., assignee/applicant, inventor, classification codes, application date, abstract, description, claims backward and forward citations, figures of technology, etc.) and their analyses is crucial for firms to have insights into different aspects of the technology developed not only by the firm but most importantly by its competitors. Thus, patent analysis becomes essential for helping managers in setting priorities, allocating resources, and reducing the risks related to new technology development (Lee, Lee, & Yoon, 2011).

Patents grant to their owners a monopoly over a specific invention, although this right is limited in time. The core importance of patents consists on excluding others from making, using, or selling the claimed invention, as such, they play an essential role in preserving the firm inventive activity efforts (Oh, Cho, & Kim, 2014). Besides, patents represent an essential source of technical knowledge as patent publications include almost 80% of all technological information of an invention (Blackman, 1995; Lee et al., 2012). In the light of the rapid and continuous change of technologies, firms face challenges related to the development, acquisition of the most appropriate new technology for a successful competition; in this context patent are widely considered a mature and objective measure (Chang, Lai, & Chang, 2009).

Furthermore, innovation scholars use patents as a useful measure of innovation performance and capabilities, especially in those industries characterized by a high density of patenting activity (Ahuja & 2001; Fleming, 2001; Hall, Jaffe, & Trajtenberg, 2001; Hall & Ziedonis, 2001; Ziedonis, 2004; Di Guardo & Valentini, 2007; Valentini & Di Guardo, 2012; Di Guardo & Harrigan, 2016; 2017; Di Guardo, Harrigan, & Marku, 2018). Indeed, patents represent the "earliest" record that detects the firms' technical knowledge on technology domains (Wuyts & Dutta, 2014). When a patent is granted, the Patent Office verifies the applicants' technological claims of novelty by searching through germane antecedent patents for evidence of intellectual origins; examiners may list patents from their searches to reflect the cumulative process by which knowledge is built (Alcácer & Gittelman, 2006; Alcácer, Gittelman, & Sampat, 2009).

The technology strategy literature has widely shown the crucial role of patents as a meaningful instrument able not only to measure the innovation performance (Ahuja & Katila, 2001; Hagedoorn & Cloodt, 2003; Trajtenberg, 1990), to capture the multifaceted dimensions of technology (Hall et al., 2001), to track the knowledge flows and spillovers (Jaffe, 1986) but also to monitor convergence and emerging technologies (Archibugi & Pianta, 1996; Curran & Leker, 2011; De Rassenfosse et al., 2013; Engelsman & van Raan, 1994; Tijssen,1992). Indeed, patent intelligence allows the transformation of the information included in a patent document into helpful insights for the business decision-making process; this represents a crucial factor for gaining a competitive advantage (Park et al., 2013).

Moreover, the body of patent literature follows two main streams for building patent indicators of the firm's technological capabilities: ex-post (information available after the application date) and ex-ante (information available at the moment of the application) measures. Most of the ex-post indicators primarily refer to forward citations in terms of technological impact or their technological classification. The number of citations received by the focal patent has been broadly used to measure the technological importance as well as patent economic value (Trajtenberg, 1990; Harhoff et al., 1999; Fleming, 2001; Hagedoorn & Cloodt, 2003; Ahuja & Lampert, 2001; Dahlin & Behrens, 2005; Hall, Jaffe, & Trajtenberg, 2005; Hedge & Sampat, 2009: Nemet & Johnson, 2012; Messeni Petruzzelli, Rotolo, & Albino, 2015; Keijl et al., 2016). Although forward citations provide useful information on the rent appropriation of an invention (Corredoira & Banerjee, 2015), they present several limitations. A patent in order to be cited requires a specific horizon of time (it might even never be cited), the patenting process requires around three years. Besides, the measure of technological impact is connected with the success of the invention per se (Verhoeven et al., 2016); indeed, a specific invention might be served as the basis for an impactful/successful invention. Also, innovation literature has built indicators to capture the firm technological capabilities ex-ante (Verhoeven et al., 2016). For instance, the value of analyzing the content of patents was suggested by Trajtenberg, et al. (1997) and has been shown to be evidence of organizational learning and technological diffusion (Dahlin & Behrens, 2005; Fleming, 2001; Fleming & Sorenson, 2001; Hall, et al., 2001).

In particular, patent maps are an effective means of discovering potential technology opportunities (Lee, Kang, & Shin, 2015). Existing studies propose two techniques to map and visualize science and technology structure, namely, patent citation analysis and patent co-classification analysis (Curran & Leker, 2011; Di Guardo & Harrigan, 2012; Karvonen & Kässi, 2013; Jeong, Kim, & Choi, 2015; Castriotta & Di Guardo, 2016; Loi, Castriotta, & Di Guardo, 2016; Marku, Castriotta, & Di Guardo, 2017). While patent citation analysis allows a more in-depth investigation of the technology flows between different elements (*i.e.*, at inventor level), patent co-classification is more suitable to map and visualize the technology structure and the connections between two or more technologies within a broad technological space (Leydesdorff, 2008; Luan, Liu, & Wang, 2013).

Method

Sample and data

The market in which a communication service provider specializes is often a function of the industry being served. These industries can be divided into three categories: telecommunications, entertainment and media, and Internet/Web services. Some communication service providers specialize, but many of them provide communication services across all major categories. Before the 1990s, communications services were highly specialized in the U.S. in the sense that there was little overlap between traditional telecom (voice), cellular, cable, and Internet companies. The U.S. Telecom Act of 1996 deregulated the provision of specialized communications services, and technology convergence began. Entry into the various service specialties brought diffusion of communications technologies that were used elsewhere. The result of this cross-pollination was a huge disruption in industry structure. The high R&D intensity showed by most firms, the high technological dynamism and complexity (Harrigan et al., 2017), as well as the digital transformation that has changed the main connotations of the industry’s core technologies, make this industry suitable for investigation.

Data on firms operating in this industry was gathered using the COMPUSTAT database (Standard & Poor's, 2013). Specifically, we used the following SIC codes to identify them: 4812 (Radiotelephone communications), 4813 (Telephone communications, except radiotelephone), 4822 (Telegraph and other message communications), 4841 (Cable and other pay television services), and 4899 (Communication services not elsewhere classified). Besides, the information on patent documents was retrieved using the Derwent World Patent Index (DWPI) focusing on a 20-year timeframe that is spanned between 1992 and 2011 (included). This procedure led to more than 120.000 patents selected and further analyzed.

Regarding the patent analysis, this study adopts the Derwent classification system instead of the most popular International Patent Classification system. The main reason was related to the possibility to extract fine-grained information from each patent document. One distinctive feature of the DWPI classification system consists of the assignment of one or multiple classification codes to the patented inventions aimed at covering all the relevant aspects (Calcagno, 2008; Harrigan & Di Guardo, 2017; Harrigan, Di Guardo, Cowgill, 2017; Harrigan, Di Guardo, Marku, & Velez, 2017; Harrigan, Di Guardo, & Marku, 2018).

The first step in the adoption of the co-classification methodology to map and visualize the technology structure, concerns the building of a frequency matrix that includes the classification codes co-occurrences that are pairs of different classification codes occurred in a patent document (Engelsman & van Raan, 1994, Curran & Leker, 2011; Karvonen & Kässi, 2013). Higher is the frequency, higher will be their technological relatedness and association strength between the technology components (Park & Yoon, 2014; Lee, Kang, & Shin, 2015). To generate the "excellence" technology structure, we identified the top-5% most impactful patents according to the number of the citations received by patents. Indeed, patent forward citations are a useful proxy for the assessment of a patent technological impact and importance (Trajtenberg, 1990; Hall et al., 2001; Di Guardo & Harrigan, 2016; Di Guardo, Harrigan, & Marku, 2018). As forward citations are strongly influenced by time, we normalized the data using the mean of the sector in each specific year accounting also for the classification code of each patent.

Multivariate analysis and visualization software

Bibliometric methods are increasingly used in innovation literature to map and visualize science and technology structure (Leydesdorff & Vaughan, 2006; Castriotta & Di Guardo, 2015; 2016; Loi, Castriotta, & Di Guardo, 2016; Marku, Castriotta, & Di Guardo, 2017; Marku & Zaitsava, 2018). In the case of patent co-classification analysis, we are interested to build a co-occurrence matrix that summarizes the frequency that two patent classification codes are included in the same patent. Then, a cluster analysis and a multidimensional scaling analysis are performed. The first is helpful to understand how technologies are gathered according to their similarity degree, while the latter allows collapsing multiple dimensions into (usually) two dimensions.

Furthermore, in this paper, we apply a novel visualization tool able not only to highlight the technology structure of the sector but also the links between the technology elements, namely, the VOSviewer software (van Eck et al. 2006; van Eck & Waltman, 2007; Waaijer, van

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Bochove, & van Eck, 2010; van Eck et al., 2010; Zupic & Čater 2015). Van Eck and Waltman (2007) introduced this new methodology to investigate the science structure according to the association strength between concepts which can be formalized as follows: $s_{ij} = \frac{c_{ij}}{w_i w_j}$, where c_{ij} represents the number of co-occurrences of items i and j, whereas w_i and w_j refer to the number of times the items i and j occur together or to the total number of occurrences of these items. The VOSviewer algorithm can be considered as a weighted multidimensional scaling that assigns to important items a higher weight than to less crucial ones (van Eck, et al., 2010).

Results

In the U.S., a communications service provider transports information electronically; for example, a telecommunications service provider suggests “voice” services. The term includes both public and private companies in the telecom (landline and wireless), Internet, cable, satellite, and managed services businesses. Figure 1 depicts the map of the industry’s technological structure in the 20-year time span (1992-2011); it further highlights not only the most critical technologies in the industry but also the most relevant links. The different swaths visualized are an indicator of the high frequency that two different technologies are included together in a patent document. Explicitly, it emerges the polycentric structure of the industry; the most-important development illustrated involves video transmission and digital computers which are prevalent throughout the twenty years as a means of operationalizing the communications services provided.

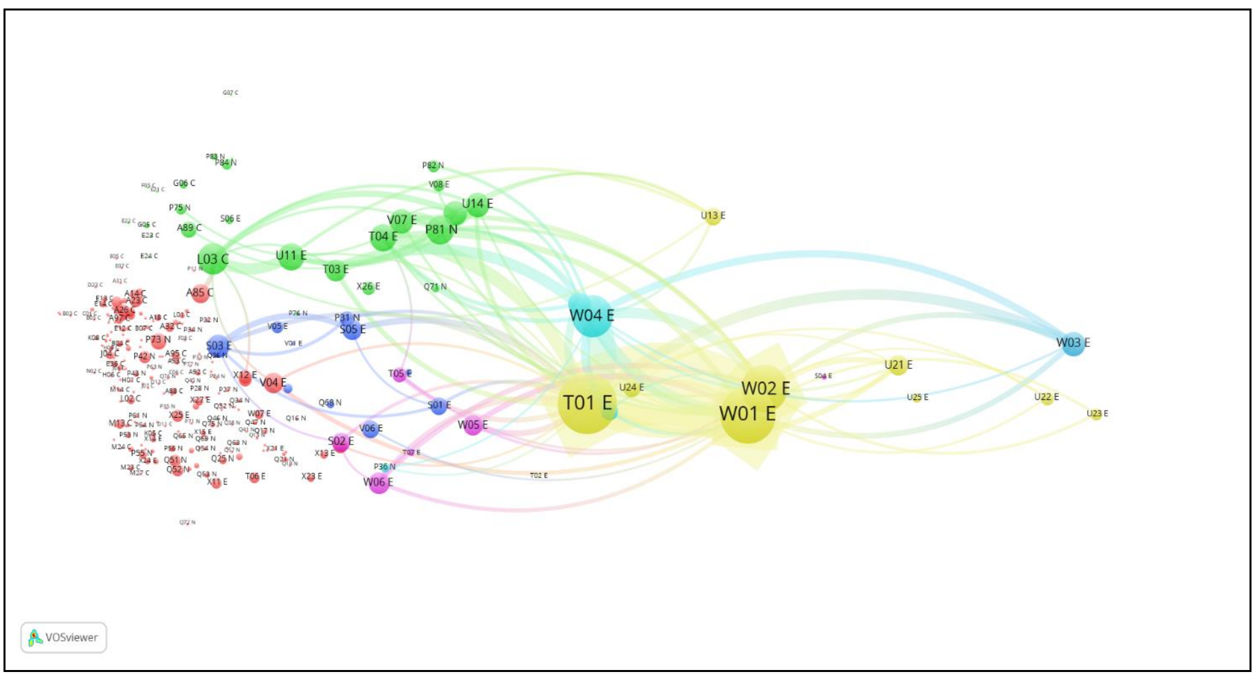

Figure 1: Technology structure 1992-2011

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More specifically, among the communications technology codes, three are most-prominent (**W01, W02**, and **W04**). The fourth code, **W03**, is of medium importance in schema. **W05, W06,** and **W07** are not prominent over the 20 years that are profiled. **W01** is telephone and data transmission systems: error detection and correction; code conversion; synchronizing; secret data communication; data networks (LAN, WAN, etc); ISDN; baseband and broadband data transmission; exchanges, call metering, test equipment, equipment racks; subscriber equipment, cordless and cellular phones; telephone line and cable installation. **W02** is broadcasting, radio and line transmission systems: aerials, waveguides, resonators and other distributed constant components; transmitters, transceivers, transponders; communication receivers; line transmission systems; radio systems, including diversity, relay, mobile (including cellular); optical and ultrasonic wave transmission systems; spread spectrum communication; secret communication, jamming; facsimile; TV systems, including color, stereoscopic, cable, subscription, satellite and high definition; stereophonic broadcast systems. **W04** is audio/video recording and systems: loudspeaker enclosures, cross-over networks; audio disc recording and reproducing equipment; audio magnetic tape recording and reproduction; sound mixers; electrical musical instruments; video cameras, camera recorders, electronic still-picture cameras; studio equipment e.g. video mixers, special effect apparatus; projection TV; video tape and disc recording and reproduction; video games, karaoke; electronic educational apparatus; sports equipment; speech coding, analysis and synthesis; antiphase sound cancelling. **T01** is digital computers: input/output arrangements and interfaces, data conversion and handling, e.g. arithmetic functions; program control and systems software e.g. program and instruction execution, operating systems, etc.; error detection and correction, computer system architecture and data transfer; distributed computing and computer networks; computer applications. **T03** is data recording: dynamic recording systems, *i.e.* based on relative movement between record carrier and transducer; analogue and digital recording on tape, disc etc, using for example, magnetic, optical, magneto-optical, capacitive methods. **P81** regards the optics technology. **L03** is electro(in)organics: chemical features of conductors, resistors, magnets, capacitors and switches, electric discharge lamps, semiconductor and other materials, batteries, accumulators and thermoelectric devices, including fuel cells, magnetic recording media, radiation emission devices, liquid crystals and basic electric elements. growing of single crystals of semiconductors and their doping are included, but semiconductor devices, where the manufacture is not claimed are excluded. There is a smaller mound of **W03** which is TV and broadcast radio receivers: AM/FM/SW radio receivers, car radios; TV receivers; teletext, high definition, satellite, stereophonic; remote control; audio amplifiers; AV systems and interconnection.

Moreover, "**U"** grouping pertains to semiconductors and electronic circuitry. **U21** pertains to logic circuits, electronic switching and coding: basic logic circuits, e.g. and-gates. A/D and D/A conversion; delta modulation, coding, code conversion, error detection and correction; pulse counters, frequency conversion; electronic switching circuits. **U22** regards to pulse generation and manipulation: rectangular wave oscillators, pulse generators; pulse shapers; digital waveform synthesizers; PAM, PPM, PFM, PDM (modulation and demodulation aspects); digital filters; DSP. **U23** concerns oscillation and modulation: oscillators, mixers; amplitude and angle (de)modulation; frequency and phase comparators; PLLs. **U24** is amplifiers and low power supplies: DC, LF and HF amplifiers, parametric, magnetic, dielectric amplifiers; gain control; volume compression or expansion; limiters; voltage and current stabilization, power supplies, converters, inverters, rectifiers; low power protection. **U25** refers to impedance networks and tuning: tone or bandwidth control. impedance converters; analogue filters (active and passive); voltage dividers, attenuators, impedance matching; tuning circuits; AFC. Additionally, **P86** includes musical instruments and acoustics. **P85** is a catch-all category for education, cryptography, adverts. **S04** pertains to clocks and timers: electronic and mechanical clocks and watches; time switches; time-interval measuring.

The different swaths visualized in Figure 1 measure the high frequency that two different technologies are occuring together in a patent document. Specifically, looking more in depth to the links between the various nodes which represent the patent classification codes, there are showed mounds of **W01** (Telephone and Data Transmission Systems) and **W02** (Broadcasting, Radio and Line Transmission Systems) close together, reflecting the increasing importance of Wi-Fi communications. These two technologies are very close to each other and interconnected with a very high frequency. **T01** is located at the center of the map showing strong connections with **W02** and **W02**; these three technologies represent the core of the sector. It is interesting to note how **T01** is almost connected with many other technologies highlighting the centrality of digital computer technology.

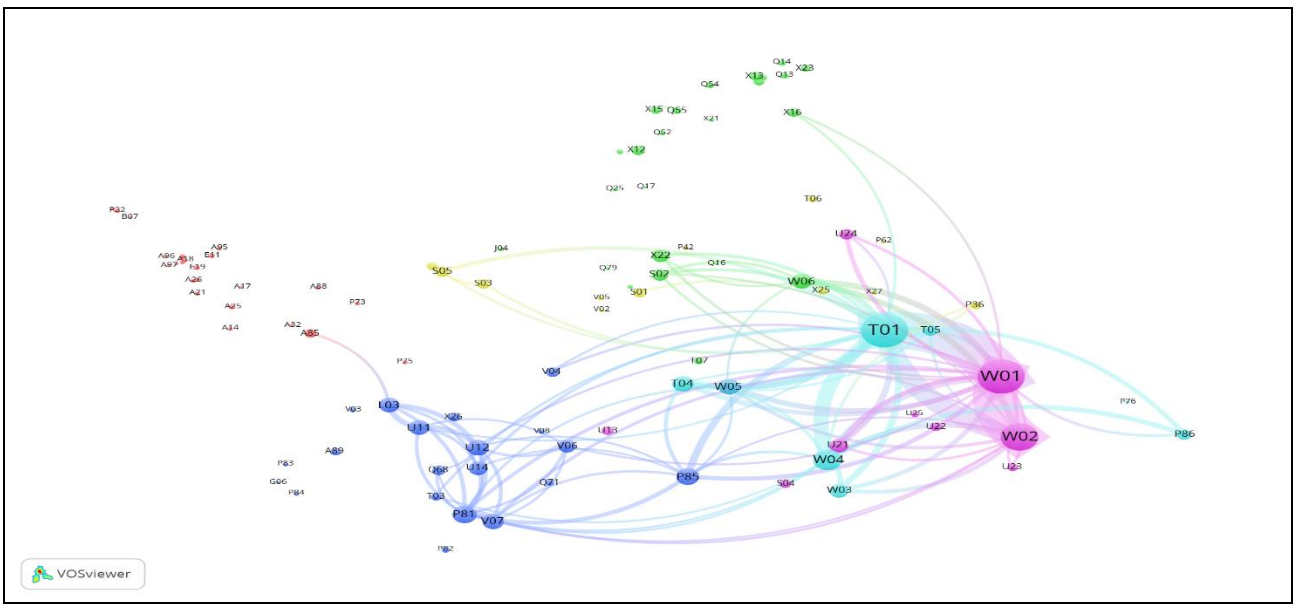

Figure 2: “Excellence” technology structure 1992-2011

To provide an additional tool based on patent analysis, our study focuses on the “excellence” technology structure. This tool allows having an overview of the technologies capable of generating high impactful inventions. It should be said that the detection of the potential

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breakthrough innovations requires time when measuring them with forward citations; however, a short time window can provide insights on technology trends.

Figure 2 shows that the industry's core technologies remain the same (**T01**, **W01**, and **W02**). It is interesting to observe that some technologies play an important role as hubs between other technologies, this is the case of **P85**, **W05**, and **V06**. Possessing technical knowledge of these technologies can be particularly useful as they are capable of being espoused and successfully included in a wide variety of patented inventions. Other technologies although have intensive links with the core are located at the margins of the map, for instance, **P86**, **P81**, **V07**, **P36**, and **U24**. The positioning at the margins of the technological space can signal the presence of technologies that are at the frontier, meaning that they have a high potentiality as well as high related risks.

Discussion and conclusion

In this paper, we introduced two patent analysis tools that can be important for firms for their decision-making process. We proposed the novel VOSviewer software to map and visualize the technology structure at a sector level. Additionally, we introduced what we called "excellence" technology structure that reveals the importance concerning centrality as well as the links between different technological elements that had a high impact on subsequent inventions.

Focusing on a timeframe that encompasses 20 years of patent activity, our results highlight a polycentric technology structure of the communications industry with a low overlap to a high-density cloud of different technologies that are positioned close to each other; this change in shape is consistent with the increase of the product complexity. Two important technologies represent the core of the industry: **W01** (telephone and data transmission) and **T01** (digital computer, data processing); they are linked by a thick swath, evidence of a strong association and relatedness. Results regarding the "excellence" technology structure showed that, as expected, the core technologies of the industry remain the same. Additionally, the map visualization allows highlighting hubs and technologies that are at the frontier.

Therefore, a firm's decision-making process is strongly related to the context in which the firm operates; hence, innovation and growth strategies should be drawn according to the knowledge profile of the sector in that specific timeframe. Our approach provides useful instruments to identify the evolution of an industry and also to help managers and firms in their strategic decisions.

In this vein, the present work contributes to the innovation literature by mapping and visualizing a technology structure in a 20-year span highlighting how digitalization has shaped the connotations of the industry. It also provides a methodological contribution by introducing two patent intelligence tools generated by the VOSviewer software that use the co-occurrence of the technology classification codes. These instruments being helpful for managers in their decision-making process also represent a managerial contribution.

Despite the contributions mentioned above, several limitations are worthy to note. In this paper, we used the information extracted from patents. As some inventions are not patented, our analysis is unable to detect the industry technological structure including information on inventions that are kept in secrecy by firms. Our study focuses on a single industry, further research may examine different industries to foster comparison between them and to detect common patterns.

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