EXPLORING THE KNOWLEDGE SPILLOVERS OF A TECHNOLOGY IN AN ENTREPRENEURIAL ECOSYSTEM – THE CASE OF ARTIFICIAL INTELLIGENCE IN SYDNEY

Abstract

New knowledge presents opportunities for commercial value and can hence be a critical asset for entrepreneurial ecosystems. In particular, general purpose technologies are major drivers of entrepreneurship, thus, a nuanced understanding on technological knowledge and its spillovers among actors within an entrepreneurial ecosystem (EE) is warranted. Using knowledge-spillover-based strategic entrepreneurship theory, we propose to observe knowledge spillovers through the assessment of the knowledge bases of a technology in an EE. To do so, this paper proposes to use three key sources of knowledge: publications reflecting the emerging knowledge base, patents representing the realized knowledge base, and startups showing the experimental knowledge base. This paper uses secondary data sources such as Web of Science and applies the method of bibliometrics to illustrate how an assessment is carried out in practice by evaluating the artificial intelligence (AI) knowledge bases in Sydney from 2000 to 2018. The findings are summarized with an illustration of the evolution of the key actors and their activities over time in order to indicate the key strengths and weaknesses in Sydney's AI knowledge among the different bases. Contrary to expectations from the high potential of knowledge spillovers from a general purpose digital technology such as AI, the paper shows that apparent knowledge spillovers are yet highly limited in Sydney. Even though Sydney has a strong emerging knowledge base, the realized knowledge base seems weak and the experimental knowledge base is slowly improving. That observation itself verifies the need to take strategic actions to facilitate knowledge spillovers within EEs. After the implications for theory and policy makers are discussed, suggestions for further studies are proposed.

Keywords: knowledge base, technical knowledge base, knowledge spillover, entrepreneurial ecosystems, Sydney, Artificial Intelligence

1 INTRODUCTION

Increasingly, research focuses on the relationship between knowledge spillovers and an entrepreneurial ecosystem (EE), in which a community of interdependent actors in a specific geographical region generates entrepreneurial activities (Acs & Sanders, 2012; Heim et al., 2019; Qian, 2017 and 2018; Scaringella & Radziwon, 2018; Subramaniam et al., 2019). However, the literature on these spillovers and their impact on EEs is in its early stages, as indicated in recent studies (Dahlstrand et al., 2019; Qian, 2018). Because knowledge spillover does not happen automatically (Qian & Jung, 2017), Ferreira et al. (2017) invite academicians and policy makers to be proactive and use knowledge spillovers for strategic purposes in order to generate innovative, risk taking, proactive and competitive business reasons. Their theory is called knowledge-spillover-based strategic entrepreneurship (Ferreira et al, 2017) and this paper adopts it in order to explore the relationship between knowledge spillovers and EEs. In particular, the paper argues that understanding knowledge bases within an ecosystem could help actors in EEs to develop strategic decisions regarding deliberate actions to improve knowledge spillovers among themselves. That is why this paper aims to focus on the assessment of the knowledge bases for a given technology within an EE in order to improve their commercial exploitation within the context of an EE.

The development of human knowledge is geographically embedded: social, economic, cultural, and cognitive environments influence social interactions and human capital (Marshall, 1898; Alvedalen & Boschma, 2017; Caragliu et al., 2011). The unit of geographical analysis might be a city, region, or country, but recent studies that examine knowledge spillovers or entrepreneurial ecosystems increasingly prefer cities or metropolitan areas (Autio et al., 2018; Cetindamar & Gunsel, 2012; Groth et al. 2015; Newman, 2017; Qian, 2018). There are also many indexes that rank cities across countries on the basis of digital technology or entrepreneurial activity (European Digital Forum, 2016). For example, the Global Startup Ecosystem Report ranks 150 cities around the globe according to their entrepreneurial performance (Global Startup, 2019).

To join the stream of studies that investigate the dynamics of a knowledge base within an EE (Helfat & Raubitschek, 2018; Qian, 2018), this paper proposes an assessment approach to evaluate the technical knowledge bases for a technology in a city and then implements it in a real-life example. Most studies in this area use the two key metrics of publications and patent databases to measure the technical knowledge present in a region (Acs & Sanders, 2012; Acs et al., 2009; Börner, 2014). Bringing the knowledge spillover theory of entrepreneurship (Qian, 2018; Ferreira et al., 2017) to bear, this paper considers startup activity as a third metric for such assessments.

As an empirical illustration of this type of assessment, this paper analyzes the knowledge bases of the general purpose digital technology called artificial intelligence (AI), which has the potential to change all aspects of production, consumption, and government services in daily life (Schwab, 2016). In addition, unlike many other digital technologies, such as robots, AI represents the invention of a method of inventing, in that it can be used to invent new applications of technology, such as autonomous driving and condition-based maintenance, and develop new pharmaceuticals (Cockburn et al., 2019). Due to its wide range of potential opportunities, AI is expected to have a massive impact on EEs (Groopman et al., 2017). In the regional context, this paper uses the city of Sydney as a rich EE because it is the site of Australia's highest concentration of technology startups, home to almost half of them, 20% of which are researching, developing, or selling in AI (Startup Muster, 2018).

This paper has four more sections. Section 2 introduces a summary of the EE concept, followed with a section presenting the relationships between knowledge bases, knowledge spillovers and EEs. Section 4 summarizes the methodology of the paper. Section 5 presents the findings related to the three knowledge sources of publications, patents and startups/entrepreneurial activities. The last section summarizes the results of the paper and ends with suggestions for future research.

2 ENTREPRENEURIAL ECOSYSTEMS

Ecosystem is a commonly used concept in biology and expresses the common life of different species in a certain environment. The boundaries may or may not be physical, but in any case they determine the inputs and outputs of the system and thus create an independent life within the ecosystem. There are critical resources in the ecosystem and actors / agents that influence the use of these resources. In other words, the ecosystem is a collaboration involving dynamic interactions between the actors' interdependence in a given environment (Adner, 2017; Susan & Acz, 2017).

The concept of ecosystem in business literature begins with the work of Moore (1993). According to Moore, the business ecosystem refers to the co-existence and close relationship of different types of firms, universities and many other corporate structures / actors in a geographically defined common environment. According to the most widely used definition, an EE is “a set of interconnected entrepreneurial actors (both potential and present), entrepreneurial organization (e.g. firms, venture capitalists, business angels, banks), institutions (universities, commercial agencies, financial institutions) and cooperation between them” (Mason & Brown, 2014, p.5).

In this paper, an EE is treated as a system in which all actors and the relationships between them are effective from the formation of opportunities to the implementation of these opportunities (Aarikka-Stenroosa & Ritalab, 2017; Van der Borgh et al., 2012). EEs might substantiate in various forms. For example, there are flexible EEs in which relations between members or stakeholders of the ecosystem are ambiguously defined, and EEs with strict rules and where all relationships are defined (Clarysse et al., 2014). The best example of inelastic EE is the “platform ecosystem” (Gawer & Cusumano, 2013). There is a main actor in this ecosystem; all other ecosystem members develop complementary products, services or technologies as part of the platform established by this actor. The most extreme example of a flexible EE is an “open innovation” ecosystem defined by spontaneous, independent actions, ultimately contributing to the development of a common innovation (Chesbrough et al., 2014; Eckhardt et al., 2018).

In the last 10 years, the studies on EEs have increased greatly. Recent studies present detailed accounts of literature reviews and their importance for different research topics, including economic development arising from EEs (Qian, 2018), the quadruple double helix model of ecosystems (Miller et al., 2016), digital EEs (Du et al., 2018; Sussan & Acs, 2017), advantages of digital platforms and open innovation system from the perspective of influx of spatial and digital abundances (Autio et al., 2018), entrepreneurship within platform ecosystems (Eckhardt et al., 2018), civil EE taking place in cities (Sarma & Sunny, 2017), policies to generate high value added entrepreneurship (Stam, 2018), evolution of EEs (Mack & Mayer, 2016), measuring EE at city levels (Audretsch & Belitski, 2017), and entrepreneurial university ecosystems (Hayter, 2016; Rodriguez-Gulias et al., 2017). There are also a few critical review of EEs indicating problems in literature ranging from concerns on definitions and underdevelopment of the concept (Alvedalen, J., & Boschma, 2017) to calling it as a 'fad' in entrepreneurship research (Brown & Mason, 2017).

In the economic literature, clusters consist of firms that share the same space, either belonging to a single sector or operating in a single technology field (Aarikka-Stenroosa & Ritala, 2017). EEs differ from clusters in two major ways: they focus on business model innovations (rather than product or technology) and they are based on optional horizontal information propagation (as opposed to vertical propagation between the user and the manufacturer) (Isenberg, 2011). Table 1 gives a detailed account of characteristics to describe an EE as a unique approach to understand entrepreneurial activities within a context.

Table 1. Dimensions of an EE

Dimensions	**Entrepreneurial ecosystem**
View of the cluster	System of entrepreneurial opportunity discovery, pursuit, and scale-up
Cluster-level economic benefit	Business model innovation and the diffusion of radical new business models in economy
Dominant knowledge spillovers	Horizontal and voluntary (sharing of experiences from business model experiments)
Role of entrepreneurs	Business model experimenters, scalers-up of successful business models
Drivers of entrepreneurial opportunity	Digital and spatial affordances to business model innovation
locus of opportunity drivers	Largely external to the cluster
Characteristic structural elements	New venture accelerators, co-working spaces, makerspaces, networking events, innovation challenges (eg. Hackathons)
Function of cluster specific structural elements	Facilitate business model experimentation and associated experience sharing, rapid scale-up of successful business models and new ventures

Source: Adapted from Autio et al., 2018.

Teece (2017) argues that knowledge commercialization is a process that involves complex or new type of organizational forms. An EE might be the new organizational form at a regional level to capture knowledge generated in a region and turn it into commercial value. In fact, Autio et al. (2018) consider EEs as a digital economy phenomenon that are explicitly organized around the entrepreneurial process of opportunity discovery, pursuit, and scale-up of new ventures. Further, the patterns and character of knowledge spillovers in EEs are characterized by horizontal, voluntary knowledge spillovers rather than vertical and operate in user-producer dyads as described in Table 1.

Alvedalen, and Boschma (2017) point out that while being a systemic concept, the EE literature is not always clear in what way the proposed elements are connected in an EE. Further, just having individual actors, institutions, and resources ready in a cluster/ecosystem do not necessarily result in system level benefits unless local knowledge networks are fully utilized (Ter Wal & Boschma &, 2011).

Based on the knowledge-spillover-based strategic entrepreneurship point of view, this paper argues that the clear understanding of knowledge spillovers necessitate a good assessment of knowledge bases creating the local knowledge stock (Qian, 2018). As discussed in the next section, understanding knowledge bases and observing spillovers offer two advantages for EEs: it could help to identify problems in knowledge spillovers that might prevent regions to turn into dynamic EE and it could show key actors in each knowledge base that might be withdrawn into strategic and deliberate action to increase knowledge flows within EE.

3 KNOWLEDGE SPILLOVERS, KNOWLEDGE BASES AND EEs

The transformation from new knowledge to economic or commercially useful knowledge usually takes one of two major forms: technology transfer or technology spillover. The former describes a transaction between a knowledge recipient and a knowledge holder at a market rate, but the latter does not involve any compensation to the knowledge holders from the knowledge recipients in relation to knowledge flow (Qian, 2018). There are numerous studies of technology transfer and even a number of dedicated academic journals, such as *The Journal of Technology Transfer*, but few publications describe technology spillovers (Bacon et al., 2019).

Some of the new knowledge created in incumbent firms or research institutions has no commercial value, so it remains unexploited (Acs et al. 2009). However, some is not perceived to be valuable due to certain constraints or filters that prevent them from flowing. The critical role that the entrepreneur plays, according to the knowledge spillover theory of entrepreneurship, is that the entrepreneur (the recipient of the knowledge) recognizes the market value of knowledge better than others and acts more quickly to commercialize it, whether actively or enabling the spilling over between economic agents, such as incumbents or other entrepreneurs (Acs et al., 2009; Qian, 2018). In other words, entrepreneurs can overcome implicit filters and allow flow.

In entrepreneurship, individuals exploit opportunities for innovation (Schumpeter, 1934) in an ecosystem, which refers to an interconnected set of organizations that are mutually dependent on each other's inputs and outputs (Subramaniam et al., 2019; Stam, 2018). Thus, the entrepreneurial ecosystem concept shows entrepreneurship as taking place in a community of interdependent actors (Oh et al., 2016). Thanks to this emphasis on actors and their interactions, the examination of EEs at the regional level might bring to light how technological opportunities are captured and existing knowledge bases can be effectively utilized through commercialization (innovation) and cluster formation (Thurik et al., 2013).

Many recent studies in entrepreneurship adopts ecosystem perspectives (Alvedalen & Boschma, 2017; Angelidou, 2014; Autio et al., 2018). However, empirical work in this area uses limited versions of this concept. For example, one study investigates the relationship between banks and universities (Ghio et al., 2019), another one shows how the regional context affects the growth of university spinoffs (Rodriguez-Gulias et al., 2017), and yet another one observes the role of maker movements in ecosystems (Eisenburger et al., 2019). Few studies investigate the major characteristics of entrepreneurial ecosystems by observing real-life examples (Isenberg, 2011; Katz and Wagner, 2014; Phillips, 2006). Another recent study focuses on case studies of a number of cities in Canada to show how ecosystems might have different configurations of cultural, social and material attributes of cities (Spiegel, 2017). Even though it is not an academic work, the Startup Genome project, which is made up of entrepreneurs, policy experts, data scientists, and community builders from the world, ranks around 150 cities' entrepreneurial performance on the basis of seven key dimensions, including performance, funding, market reach, connectedness, talent, experience, knowledge, and growth index since 2012 (see details at http://Startupgenome.com and Global Startup Ecosystem Report, 2019).

In a similar vein, Qian (2018) identifies five factors that are important for the functioning of EEs: knowledge bases, competition, networks of individuals, diversity of related industries and of people, and culture, understood as a multidimensional concept, formed of willingness to collaborate, openness, hierarchy, social capital, and organizational culture in universities. He further argues that differentiated knowledge bases represent differentiated entrepreneurial opportunities that therefore result in regional variation in knowledge-spillover entrepreneurship. For this reason, he and his colleagues (Qian and Jung, 2017; Qian, 2017) have conducted a number of empirical studies where they measure knowledge by using skill databases to identify different sets of knowledge, such as management knowledge, engineering knowledge, and so on, within a region.

Inspired by Qian's works and the theory induced by Ferreira (2017), this paper aims to shed light more on the knowledge dimension of an EE. In order to observe knowledge spillovers, one has to first find out what knowledge is created in that ecosystem. Hence, our contribution to the EE literature rests on offering an assessment of knowledge bases for a given technology within an EE. In order to quantify knowledge, this paper focuses on a given technology for two reasons. First, choosing a single domain of technology can allow an in-depth assessment for observing a spillover phenomenon within that knowledge base. Second, recent studies have found that a wide range of affordances arise from digital technologies, necessitating a nuanced approach to the observation of technical knowledge in an EE, especially in the field of digital technology (Autio et al., 2018). In fact, digital technologies are increasingly being seen as key drivers of entrepreneurial ecosystems because technological affordances arising from digital technologies can facilitate the pursuit of entrepreneurial opportunities by new ventures (Attaran, 2017). For this reason, some recent studies have gone a step further and even coined the term "digital entrepreneurial ecosystems" to reflect a greater emphasis on entrepreneurial ecosystems that are generated by digital technology (Du et al., 2018; Sussan & Acs, 2017). But it seems, there are by far no particular studies assessing a specific technology at an ecosystem level. Most of the studies and indexes mentioned above treat technology/knowledge as a general category. For example, the Global Startup Ecosystem Report (2019) considers knowledge as a combination of high levels of creation of tangible intellectual property in the form of patents, research, and favorable policy environments induced by national government. However, considering knowledge at such a high level might prevent observing the real dynamics taking place at individual technologies. This might oversight the observation of knowledge spillovers within a region.

Digital technologies encompass a wide range of advances, some with highly limited applications (e.g., 3D printing) and others with a wide range of applications across industries (e.g., AI) (Scwab, 2016). This paper investigates AI, a general purpose digital technology that will initiate horizontal spillovers, simultaneous occurrence of both scientific and innovation activities through their interactions with each other as expected by the EE literature (Autio et al., 2018). AI refers to a set of interrelated technologies including machine learning, computer vision, human language technologies, and robotics, which aim to solve problems autonomously and perform tasks that can achieve a group of objectives without explicit guidance from human beings (Hajkowicz et al., 2019). Thus, AI is an invention of a method of inventing, in that AI can be used to invent new techniques, such as autonomous driving and condition-based maintenance, and to develop novel pharmaceuticals (Cockburn et al., 2019). AI has been successfully implemented in several fields, including industrial robotics and autonomous operation technologies, investment decisions for financial institutions, financial advisory work, and in cleaning robots and AI speakers (Motohashi, 2018). For this reason, Schwab (2019) says that the AI revolution is "unlike anything humankind has experienced before," due to four particular characteristics: mobility, situation awareness, adaptivity, and real-time communication with other intelligent machines.

Because local knowledge largely comes from three key ecosystem agents, namely researchers, inventors, and entrepreneurs, we suggest that a local technical knowledge base can be assessed by capturing the contributions of these key actors through publications, patents, and entrepreneurial activities. Publications and patents are commonly used in the literature (Motohashi, 2018; Quai, 2018). Our approach introduces the third metric of entrepreneurial activities, accounted for by measuring the number and scope of AI startups. This metric reflects the experimental knowledge generated from trial-and-error experiments carried out by entrepreneurs who work specifically with AI technology (Jha, 2016). As Lindholm-Dahlstrand et al. (2019) describe it, entrepreneurs supply a micro-level mechanism for system-wide entrepreneurial experimentation that creates, selects, and scales up new technology and innovations within an innovation system. Further, they argue that entrepreneurial experimentation relates to both market and technical experimentation; because of this, they consider experimentation to be a key function of entrepreneurs in an entrepreneurial ecosystem, helping to build knowledge in a specific technology. Following the lead of recent studies (Goel & Saunoris, 2017; Qian, 2018; Rodriguez-Gulias et al., 2017; Schillo, 2018), we propose startups as a proxy measure to reflect ongoing experimentation in our study. In sum, we argue that the assessment of a technical knowledge base through counting its publications, patents, and startups could provide a good picture of the knowledge base that exists in a region.

Companies, researchers, and entrepreneurs are located in certain environments, whether these are understood as regional or urban, that have different contextual factors, which shape their activities (Asheim et al., 2011; Chakrabarty & Bass, 2013; UN, 2017). For this reason, researchers note the role of local conditions and bottom-up processes and suggest that policies be customized for the given entrepreneurial regional economy with the selection of a regional unit to focus on (Groth et al., 2015; Stam, 2015). For example, in 2016, the EU launched its Digital Innovation Hubs initiative at the regional level to reduce disparities between regions in their information uptake and communication technologies for small and medium-sized companies (Gianelle et al., 2016; Radosevic & Stancova, 2018). This type of approach can identify areas of discovery and mobilize stakeholders to discover, in a collaborative manner, where potential exists for regional growth.

For this reason, recent studies that have examined knowledge spillovers and EEs have used cities for their unit of regional demarcation (Qian, 2018). Many cities are in competition with each other globally, and some clearly lack integrative policies that could orchestrate capabilities and stakeholders to generate comparative advantages (OECD, 2013; Roger et al., 2015; Stam, 2015). Thus, an assessment focused on knowledge bases could help policy makers and leading stakeholders consider the creation of integrative EE in which entrepreneurs could tap into the knowledge bases for digital technologies and speed their utilization in a given region. This is a main reason why the EU is supporting the measurement of entrepreneurship in 70 EU cities through the Regional Entrepreneurship and Development Index (Audretsch & Belitski, 2017).The same line of thinking was adopted at measuring global cities by using data collected for Global Entrepreneurship Monitor (Acz et al., 2018).

In sum, considering that the assessment of technical knowledge in EEs is in its early stages, this paper offers a framework in which to assess AI’s potential for the EE in a city, as shown in Figure 1, which is based on three data sources: publications indicative of the new knowledge being generated (emerging knowledge), patent data indicative of tacit knowledge being transformed into codified knowledge by becoming intellectual property (realized knowledge), and startup data that show the market and technical experimentation resulting from new knowledge (experimental knowledge).

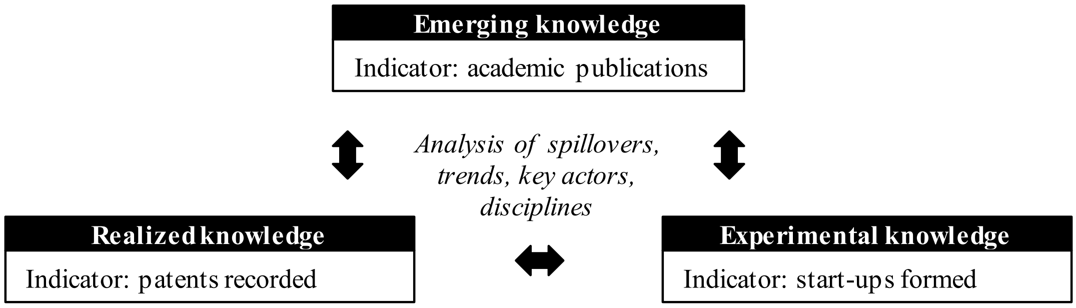

Figure 1: Framework for knowledge base analysis

4 METHOD

4.1 Context of the Study

As in many countries, AI is a critical technology for Australia. Accordingly, it is estimated that digital technologies, including AI, may become worth as much AU$315 billion to the Australian economy by 2028 (Hajkowicz et al., 2019). In 2018, the Australian Government announced an initiative of AU$29.9 million to advance AI and machine learning in the country, and, since 2010, the Australian Research Council has awarded more than AU$243 million to pure research projects classified as AI and image processing (Hajkowicz et al., 2019).

This study is an empirical investigation of the city of Sydney, Australia, to determine how best to assess the technical knowledge base of AI. Sydney is the only city from Australia that is in the top 30 entrepreneurial cities in 2018, ranked 23rd (Global Startup, 2019). Around 1500 startups are registered in Australia, and almost half of them are in Sydney (Startup Muster, 2018). Further, Sydney hosts a wide range of industries and internationally known universities, hence it has good access to the skills, creativity, and talent needed for digital EE (Startup Genome, 2017). In 2017, Sydney featured the highest rate of digital inclusion of any capital of an Australian state or region (Thomas et al., 2017). Sydney's population shares this perception, with 58% of Sydney residents reporting that Sydney is digitally advanced (the highest rate of any Australian city) (EY Sweeney, 2017). The proximity of individuals to each other within a city for exchange of knowledge and for driving innovation remains important, even in the digital era. This is true for Sydney in particular, which currently holds top rank among knowledge cities in Australia (Pratchett et al., 2017). Finally, 20% of startups in Sydney are working in AI (Startup Muster, 2018), and 89% of all AI jobs in Australia are in Sydney and Melbourne (Hajkowicz et al., 2019).

Aiming to explore the knowledge spillovers of AI in Sydney's entrepreneurial ecosystem, three kinds of knowledge (i.e., emerging knowledge, realized knowledge, and experimental knowledge) will be investigated through three data sources (i.e., publications, patents, and startup datasets). Whereas the advantages of bibliometrics in quantitatively analysing scientific documents (e.g., publications, patents, academic proposals, and technical reports) and statistically describing historical events in scientific and technological areas (Hood & Wilson 2001) - e.g., profiling technological landscapes and identifying technological components (Guo et al. 2009; Zhang et al. 2016), and detecting and tracking technological evolution (Zhang et al. 2017), bibliometrics have been widely used for discovering knowledge and empirical insights from such scientific documents, and thus, it is selected as the core methodology of this study.

4.2 Bibliometrics as core methodology

Bibliometrics emphasize the use of bibliographical indicators, such as citation statistics, text segmentation, and authorships (Rafols et al. 2010), and this study is to discover key players in the given field and also relies on text segmentation to understand the key research topics and their relationships.

Authorship is the sphere of information that involves authors and co-authors, their affiliations, and their related geographical information. Text segmentation is the analysis of text retrieved from a document through natural language processing (NLP) techniques. Once retrieved, the raw text is pre-processed with a term clumping technique to remove noise and consolidate technical synonyms from a combination of rules and expert knowledge (Zhang et al. 2014). Co-word analysis was first proposed by Callon et al. (1983) on the hypothesis that, if two words frequently appear together, they are similar. Co-word analysis is typically the first step in measuring the relationships within and between the groups of words and phrases that make up topics, i.e., domains of scientific research (Noyons & van Raan 1998).

Co-word analysis belongs to a branch of bibliometrics called co-occurrence analysis. The corresponding algorithm is described as follows.

- Assuming a list of elements $E = \{e_1, \dots, e_i, \dots, e_n\}$ might either be a list of words or a list of authors, an element e_i can be represented as a co-occurrence vector $C_i = \{c_{i,1}, \dots, c_{i,i}, \dots, c_{i,j}, \dots, c_{i,n}\}$, in which $c_{i,j}$ is the frequency of the co-occurrence between the elements e_i and e_j.
- The similarity $s(e_i, e_j)$ between the elements e_i and e_j, can then be calculated by Salton's Cosine measurement (Salton & McGill 1986), i.e.,
    - $s(e_i, e_j) = Cos(C_i, C_j) = \frac{C_i \cdot C_j}{|C_i||C_j|}$
- The output of the co-occurrence analysis is a triangle similarity matrix S that records the similarities between all pairs of elements in the list E.

The similarity matrix S is, in effect, a science map (see Figure 2). Science maps are a tool for visualising bibliometric results that represent the relationships among disciplines, fields, specialties, and individual papers or authors in spatial terms (Small 1999). Their power for illustrating the extent and structure of large-scale data has proven promising. As such, they are quite helpful for understanding scientific activities, innovative pathways, and interactive relationships (Börner 2014).

Algorithmically, a similarity matrix S can be mapped as a graph $G = \{E, L\}$, in which E and L respectively represent the sets of nodes and edges in the graph. Each node is represented by one element (either an author or a word/phrase), and the edge between two nodes e_i and e_j is weighted by $s(e_i, e_j)$. Thus, similar nodes are placed close together, and a group of similar nodes usually reflect particular meanings, e.g., collaborative groups, research topics, etc.

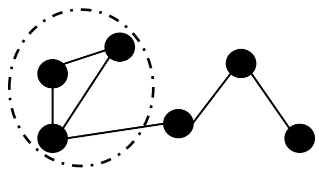

Figure 2: A simple science map

The justification of bibliometrics has been fully discussed by the bibliometric community from both quantitative and qualitative aspects. Initially, based on statistics, bibliometrics objectively describe status, trends, and their changes through numbers (Zhang et al. 2013), such as how many articles one university has ever published and how such a number changed over time. It is clear that such facts reflecting the reality do not require additional validation. Furthermore, bibliometric approaches, such as co-word analysis and science maps, have been experimentally and empirically examined in a large number of cases and have been widely accepted as a mature tool in bibliometrics - e.g., co-word analysis was exploited to map the structure of a given discipline (Ding et al. 2001) and grasp the dynamics of a research topic over time (Ronda - Pupo & Guerras - Martin 2012), and science maps further extend the scope of co-word analysis in a vivid way (Peters & van Raan 1993) and their performance in mapping the backbone of sciences has been well evaluated and discussed (Boyack et al. 2005). Given the circumstances, the bibliometric methodologies used in this study have already been well justified and discussed in the literature, and have been used as an extensive and quantitative supplement for expert knowledge-based studies.

4.3 Databases and search strategies

As the most representative bibliometric database, the Web of Science (WoS) Core Collection was selected as the data source for analysing publications (more information can be found on the website: https://clarivate.com/webofsciencegroup/solutions/web-of-science/). The WoS originated from the Science Citation Index and has become one of the most relied upon and powerful databases in the bibliometric community. The WoS is famous for its broad collection – it contains over 21,100 high-quality, peer-reviewed scholarly journals in more than 250 scientific disciplines, with approximately 74.8 million academic articles and 1.5 billion cited references dating back to 1900. A large number of bibliometric studies has been performed based on WoS sources, so the analytical methods, approaches, and software tools associated with this corpus are relatively mature and trustworthy.

Referring to a report investigating the development of Australia's AI research from 2000 to 2018 (Zhang et al. 2019), we followed its search strategy, which focuses on the use of the WoS Categories (see Table 2). #1 reflects the backbone of AI research, #2 considers the applications of AI techniques, and #3 includes AI-related theories, concepts, and algorithms. A city-based refinement via VantagePoint, which is a commercial software used in text mining and particularly in science, technology and innovation text analysis (see details at the website: https://www.thevantagepoint.com/) was conducted and collected 6,959 publications.

Table 2: Search strategy of collecting AI-related publications affiliated with Sydney (Note: WC = Web of Science Category)

No	Search strategy	# records
#1	WC= "Computer Science, Artificial Intelligence"	7,507
#2	WC= "Computer Science, Information Systems"	7,310
#3	WC= "Computer Science, Theory & Methods"	6,384
#4	#1 OR #2 OR #3	18,050
#5	City = "Sydney" in #4*	6,959

For the patent analysis, we chose the United States Patent and Trademark Office (USPTO) as shown in Table 3. The market of the United States is considered as the key for technology transfer and global commercial potential. Thus, the USPTO becomes a premier patent office in which inventors file their patent applications with priorities (Zhang et al. 2013). The USPTO has successfully been chosen to serve as a proxy for worldwide IP by studies in the past. Another option would have been to use the Derwent World Patents Index, however the database does not classify its patents according to an affiliation with a city.

Compared to the use of the WoS Categories for proposing the search strategy for collecting AI-related publications, the International Patent Classification (IPC) codes provide a hierarchical taxonomy system to classify technologies (Zhang et al. 2018). Please not that for the IPC codes a different acronym (ICL) is used in the context of the USPTO. Aiming to maintain similar structures of search strategies for publications and patents, this study uses an IPC-based search strategy for collecting AI-related USPTO data, with the aid of expert knowledge from the Centre for Artificial Intelligence, University of Technology Sydney. The selected IPCs closely relate to AI algorithms, technologies, and approaches, such as the ICL code 'G06F 17' refers to digital computing and data processing equipment and methods.

Table3: Search strategy of collecting AI-related patents affiliated with Sydney

Search strategy	# records
ICL/(G06F15$ OR G06F16$ OR G06F17$ OR G06K$ OR G06N$ OR G06Q90$ OR G06T7$ OR G06T9$) AND IC/(sydney) AND APD/1/1/2000->12/31/2018	165

Description	Code
International Classification (This field contains the International Classification(s) to which the patent has been assigned.)	ICL

Digital computers in general; data processing equipment in general	*G06F15*
Information retrieval; database structures therefor; file system structures therefor	*G06F16*
Digital computing or data processing equipment or methods, specially adapted for specific functions	*G06F17*
Recognition of data; presentation of data; record carriers; handling record carriers	*G06K*
Computer systems based on specific computational models	*G06N*
Systems or methods specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes, not involving significant data processing	*G06Q90*
Image analysis	*G06T7*
Image coding	*G06T9*
Inventor City (This field contains the city of residence of the inventor at the time of patent issue)	IC
Application Date (This field contains the date when a complete application was received by the US Patent and Trademark Office)	APD

For the analysis of the AI-related startup landscape in Sydney, we used a dataset provided by Traxn company, which is a research partner for Venture Capitalists and Corporate Development offices powered by the largest Startup Data platform tracking over 10m companies globally. As of 17 September 2019, it contained 117 startups. As with publications and patents, a co-occurrence analysis of keywords was performed on that dataset.

5 THE ANALYSIS OF AI KNOWLEDGE BASES AND SPILLOVERS IN SYDNEY

By analysing the three different knowledge bases for AI in Sydney, we will try to shed light on the dynamics of each knowledge bases and potential knowledge spillovers among them.

5.1 Publications network as indicator for the emerging knowledge base

Looking at academic publications as indicators of emerging knowledge in the field of AI in Sydney, Table 4 provides an overview of key contributors.

Table 4: TOP10 Author affiliations, Funding Organizations and Journals with most AI-related publications for Sydney

Rank	Author Affiliation	# records	Funding Source (Country)	# records	Journal	# records
1	UNSW	1579	Australia	1522	IEEE Trans. Image Process.	200
2	Univ Technol Sydney	1542	China	1407	IEEE Access	181
3	Univ Sydney	1372	US	156	Neurocomputing	151
4	Univ Wollongong	826	EU	125	Pattern Recognit.	121
5	Macquarie Univ	573	Canada	37	IEEE Trans. Neural Netw. Learn. Syst.	118
6	Univ Newcastle	444	Korea	27	Inf. Sci.	115
7	CSIRO	371	Singapore	24	IEEE Trans. Knowl. Data Eng.	103
8	NICTA	343	UK	7	Theor. Comput. Sci.	101
9	Univ Western Sydney	303	Japan	6	IEEE Trans. Inf. Theory	96
10	Chinese Academy of Science	239			Expert Syst. Appl.	95

Unsurprisingly, universities based in the Sydney metropolitan region dominate the academic output. They are accompanied by the national research bodies The Commonwealth Scientific and Industrial Research Organisation (CSIRO), Australia's Information and Communications Technology Research Centre of Excellence (NICTA) as well as the Chinese Academy of Science, pointing at a strong collaboration between Australia and China in the field of AI research. This collaboration is further corroborated by the countries providing funding to AI-related research in Sydney. Funding from China was involved in almost as many publications as funding from Australia. Notable, but significantly lower funding connections exist with the United States and the EU. As for the funding from Australia, the highest share of funding (1,352 records) is received through government bodies (such as the Australian Research Council). Funding from universities themselves sits at 171 records, while funding through industry-related schemes counts 99 records (please note that some records may have several funding organizations). This points into the direction that, for the case of AI, a significant share of research is still exploratory, and the share of applied research is still quite low in comparison. Regarding AI-related journal publications, a high level of academic quality of the research output can be confirmed. All those journals sit in the top quarter of journals for Computer Science or Artificial Intelligence respectively in the SCImago Journal & Country Rank.

Table 55 lists the TOP 20 keywords used in AI-related publications affiliated with Sydney and their evolution over time. The keywords cover special branches of AI (e.g. machine learning, optimization), application areas (e.g. wireless sensor networks), and issues (e.g. privacy). A very strong focus on cloud computing becomes visible, showing 50% more publications than the second rank. Over time, some areas are showing consistent output (like optimization) or slow and steady growth (like genetic algorithm). Others have spiked and are declining (like performance, referring to the efficiency, accuracy and robustness of computational models) and others have just come up recently and grown rapidly since then (like cloud computing and classification). The big data boom started in the late 2000s and cloud computing could be considered as a technical breakthrough associated with big data (Martin, 2019). Also, this boom led to a rise in privacy as increasingly emergent issue in both the computer science and social science -areas. Neural networks initially appeared in the literature decades ago, but soon became a 'sleeping beauty' due to the lack of sufficient computational powers. However, the rapid development of computer hardware, as well as deep learning techniques, recently ‘awoke’ neural networks as a field which can now be considered one of the hottest topics in the AI area. Certain traditional tasks in the area of computer science maintain a relatively stable trend in the past decades, such as classification, cluster analysis, and feature extraction/selection, but the further development of AI techniques may provide new solutions to these tasks.

Table 5: TOP 20 keywords for AI-related publications in Sydney (as provided by authors overall and per year)

Rank	Keyword	Overall	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18
1	cloud computing	123											2	4	9	13	13	24	17	18	23
2	Algorithms	80	2	1	2	1	3		4	1	1	5	3	8	5	12	4	10	9	7	2
3	Classification	76						2	1	2	1	1	2	5	6	4	5	5	12	15	15
4	wireless sensor networks	69						1		1		4	5	2	4	9	10	3	7	12	11
5	cluster analysis	67			2	2	3	2	1	4	2	4	1	3	1	6	7	7	6	5	11
6	neural network	67	3	5	2	1		1			1	3	3	5	5	7	4	7	6	5	9
7	Performance	63		1			1		2	3	1	4	3	6	4	8	4	9	11	4	2
8	genetic algorithm	59		2	3	3	3	2	2	1	4	2	3	3	2	6	3	5	3	4	8
9	machine learning	59			1	2	1	2	2	4	1	1	2	1	4	5	2	7	6	5	13
10	data mining	58		2	2	2		2	3	2	3	2	3	3	7	5	4	3	5	5	5
11	Security	52				2	1	2	1		1		4	6	5	4	3	7	10	4	2
12	Optimization	51		3	1		2		1	5	6	3	3	4	3	4	4	2	4	2	4
13	Scheduling	48		1		1	2	1	1	1	3	1	3	3	6	3	7	5	2	2	6
14	big data	47														2	8	11	7	12	7
15	knowledge representation	47		1	1	4		3	3	2	1	2	3	2	8	2	1	4	1	5	4
16	Privacy	47				1	1	3	1		1		3	4	5		5	5	7	6	5
17	Design	46		1	1		1		1	2	1	2	5	4	1	10	5	3	7	2	
18	feature selection	43									1	1	2	3	1	5	6	5	6	4	9
19	feature extraction	41	2			1		2	1		1	2			4	3	3	4	4	6	8
20	recommender system	41			1					1					2	6	2	10	8	6	5

Figure 3 highlights certain key research emphases of Sydney's AI researchers.

- machine learning & data mining - these techniques interactively connect with each other and lay on the left side of the figure, and certain highlighted nodes include deep learning and transfer learning, fuzzy set and fuzzy systems, decision making, and neural networks

- cybersecurity - the majority of this area consists of the green nodes on the right side of the figure, which not only cover certain important information technologies, such as encryption, cryptography, and access control, but also public concerns on data privacy
- cloud computing - cloud computing is a key area in data engineering and software engineering, in which machine learning and data mining techniques are heavily involved - see the overlay yellow nodes on the left side of the figure. Also, as a backbone of internet-of-things, concerns on the privacy issue of cloud are still on debate these days - it explains why the node of cloud computing is geographically close to the node of privacy as well.

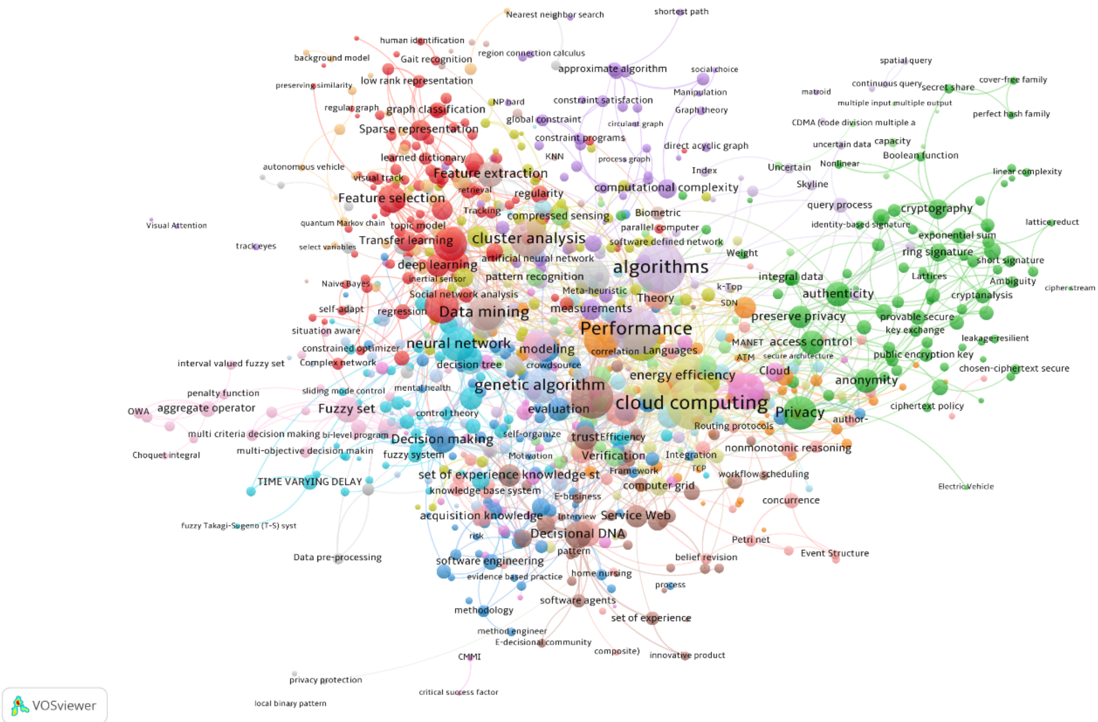

Figure 3: Co-word map for AI-related publications affiliated with Sydney

5.2 Patent network as indicator for the realized knowledge base

For AI-related patents with connection to Sydney, Table 6 shows the TOP companies and country location of assignees based on the number of patents filed.

Table 6: TOP companies and locations for AI-related patents affiliated with Sydney

Rank	Company	# records	Location of Assignee	# records
1	Google	27	US	104

2	IBM	20	AU	46
3	Atlassian	12	CA	4
4	Citrix Systems	8	DE	3
5	Avaya	6	GB	3
6	Honeywell International	4	JP	3
7	Toyota	4	CN	1
8	University of Technology Sydney	4	NL	1

Six of those eight companies are American, one is Japanese (Toyota) and one an Australian research institution (University of Technology Sydney). Except the latter, all those companies can be considered to be big international corporations. AI-related patents seem to mostly be IP generated on behalf of overseas business in collaboration with Sydney-based inventors. This is confirmed by the fact that most patents, despite being filed in collaboration with Sydney-based inventors, belong to US-based assignees. However, out of the 165 patents, around on quarter belongs to Australian-based assignees. One final observation is the fact that even though China is the major collaborator in academia by giving funding to research carried out in Sydney, there is only one Chinese patent assignee. This indicates that international relations in one knowledge base does not necessarily result in a spillover to another one. In addition, it might flag that international collaborations might be tapping into local fundamental knowledge base and then utilize it in their own countries in the form of patents or startups, representing a flight of knowledge to other entrepreneurial ecosystems.

Table 7 now shows the TOP 20 keywords and their temporal evolution mentioned in AI-related patents affiliated with Sydney (similar to Table 5 for publications). Given the overall low number of patents identified through the search, the temporal evolution of keywords seems skewed. It is common practice for inventors to file several version of their IP using very similar descriptions. This is likely the reason for the multiple identification of keywords within the same year (e.g. access credentials in 2013). Based on these considerations, a co-word map for patents was not generated. Overall however, we remain confident that the search strategy is correct. For comparison, the same strategy has yielded 883 results for Berlin and 5,028 results for Beijing.

Table 7: TOP 20 keywords for AI-related patents affiliated with Sydney (retrieved from combined areas of title and abstract using NLP; overall and per year)

Rank	Keyword	Overall	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18
1	Embodiments	25					1			2	4	2	3	2		1	2	2	2	2	2
2	computer program product	21		3						2			3	2	1	4	1	2	2	1	
3	access credentials	7														6		1			
4	connected devices	7														6		1			
5	devices function	7														6		1			
6	enterprise application store	7														6		1			
7	enterprise resources	7														6		1			
8	interconnected devices	7														6		1			
9	management policies	7														6		1			
10	multiple devices	7														6		1			
11	operation modes	7														6		1			
12	orchestration framework	7														6		1			
13	policy agent	7														6		1			
14	respective applications	7														6		1			
15	digit image	23			3	2	1			1		1		1					6	1	3
16	video stream	23			2	2	4			1			1			2	2	2	3	2	
17	computer program product	21	1		3	2	2			2			1	1		1	1	2	1	2	2
18	internet-of-Things (IoT)	21	1	4	2	2			1				1		2		2	1	1	1	3
19	machine learning algorithm	21			1				1						1	1	2	4	3	2	6
20	Controller	20	1	2	2	1	2	1			1		1	1			1	1			3

Intriguingly, it may be due to the commercial and legal meanings of patents, that the TOP 20 terms retrieved from patents are relatively ‘broad’ - i.e., applicants use relatively general terms (such as connected devices or video stream) to describe their key technologies, rather than specific algorithms (such as neural networks, genetic algorithms, and feature extraction).

Overall, compared to terms retrieved from publications, terms in patents indicate a relatively high level of application-driven or commercialization-driven style, rather than pure techniques and algorithms. It seems that Sydney’s AI publications are touching the research frontiers and cutting-edge areas of AI, such as neural networks and machine learning, but Sydney’s AI patents, comparably, show a closer relation to information systems (e.g., data collection, data processing, and data storage) rather than AI algorithms (e.g., data analytics).

Sydney’s AI patents also indicate that Sydney’s AI companies (or maybe research teams who aim to conduct technology transfer at certain points) are relatively isolated and focusing on individual projects, devices, and techniques. In other words, Sydney has not built up a systematic AI industry from a patent point of view.

5.3 Start-up base as indicator for the experimental knowledge base

We will now analyse the startup ecosystem in Sydney and shed light on the possibility of knowledge spillovers form the previous analyses of publication and patents.

Table 8 lists the TOP 10 Sydney-based startups in the area of AI according to the amount of funding received. These startups focus on a range of AI-related business models with a perceived focus on machine-learning-enabled visualisation and data analytics platforms. It does not surprise that the startup with the highest funding works in the financial technology sector, given Australia's, and specifically Sydney's, leading role in this field (Global Financial Centres Index, 2019).

Table 8: TOP 10 Sydney based AI startups based on funding received

Rank	Company Name	Description	Founded Year	Funding (mUSD)
1	Xinja	Australian-based neo bank	2017	14
2	Hyper Anna	Machine learning for data analytics and visualization	2016	14
3	Oovvuu	Online video marketing and syndication platform	2013	9
4	Encompass	KYC automation software	2011	5
5	Lumachain	Integrated supply chain visibility platform	2018	4
6	Curious Thing	AI-based conversational candidate assessment solution for volume hiring	2018	4
7	EARTH AI	Develops a machine learning-based data analytics platform for mineral exploration using multiple layers of data	2016	3
8	myInterview	Cloud based video interview platform	2014	2
9	Particular Audience	Consumer intelligence solution	2017	2
10	BRiN	Offers personalized business education content through both a chatbot and an app interface	2016	1

Source: https://tracxn.com/explore/Artificial-Intelligence-Startups-in-Sydney/ [accessed 19 Sep 2019]

Similarly to before, Table 9 now shows the TOP keywords used to describe AI-related startups in Sydney. Besides the obvious terms of artificial intelligence and machine learning, two key focus areas seem to emerge – one around the application are financial technology ("financial decision making" and "blockchain") and one around the method of data analytics ("big data" and “data mining”). As a method, data analytics also features prominently in the publications (e. g. “data mining” and “big data”), confirming a potential knowledge spillover. Strong research outputs in “cloud computing” and “wireless networks” however do not seem to find representations in the business models of local startups.

Table 9: TOP10 keywords for AI-related Sydney-based startups (retrieved from the dataset using NLP)

Rank	Keyword from Description	# records
1	machine learning	16
2	artificial intelligence	13
3	big data	7
4	financial decision making	4
5	blockchain	3
6	data mining	3
7	facility managers	3
8	inventory manager	3
9	AI-based technology	2
10	automated reports	2

The co-word map for Sydney-based startups involved in AI in Figure 4 reveals some interesting thematic clusters around the core concepts of artificial intelligence and machine learning. While one cluster unsurprisingly emerges around financial decision making, data mining and recruitment, another stream seems to focus on operations management (including “facility management”, “supply chain”, “prediction maintenance” and “inventory management”).

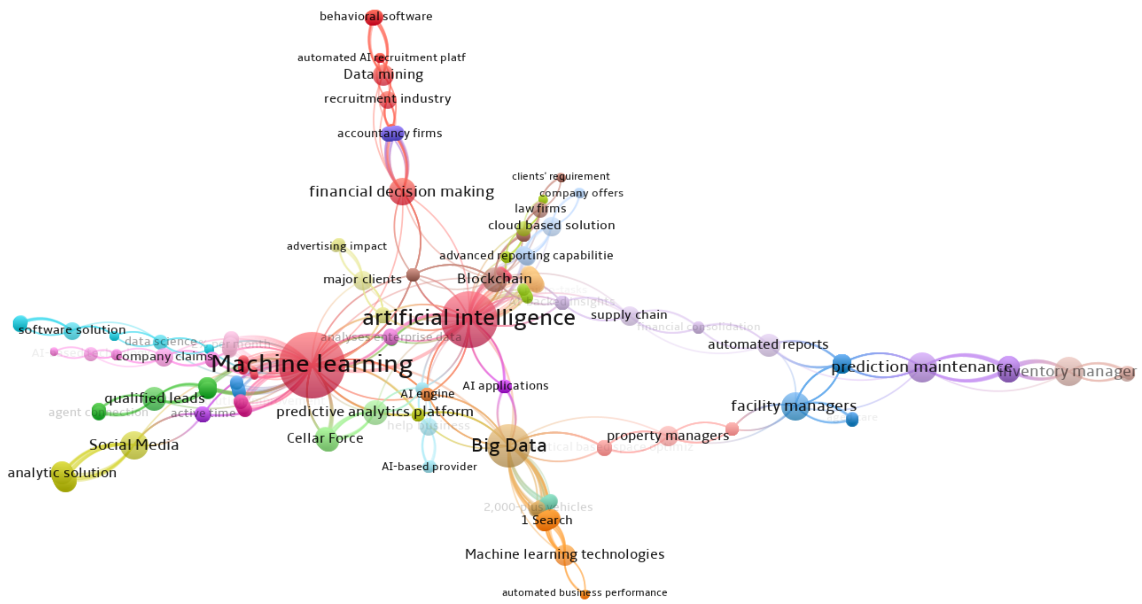

Figure 4: Co-word map for AI-related Sydney-based startups

Finally, Figure 5 puts the temporal development of all three knowledge bases in context. As expected, the number of publications as an indicator for emerging knowledge is consistently higher than the proxies for the two other knowledge bases. Also, there is a very visible decline between 2005 and 2007. This could hint at a short "cold era" of AI development due to a lack of required computational performance power at the time. However, after that dip, the publications show by far the sharpest rise in output compared to the other two knowledge bases.

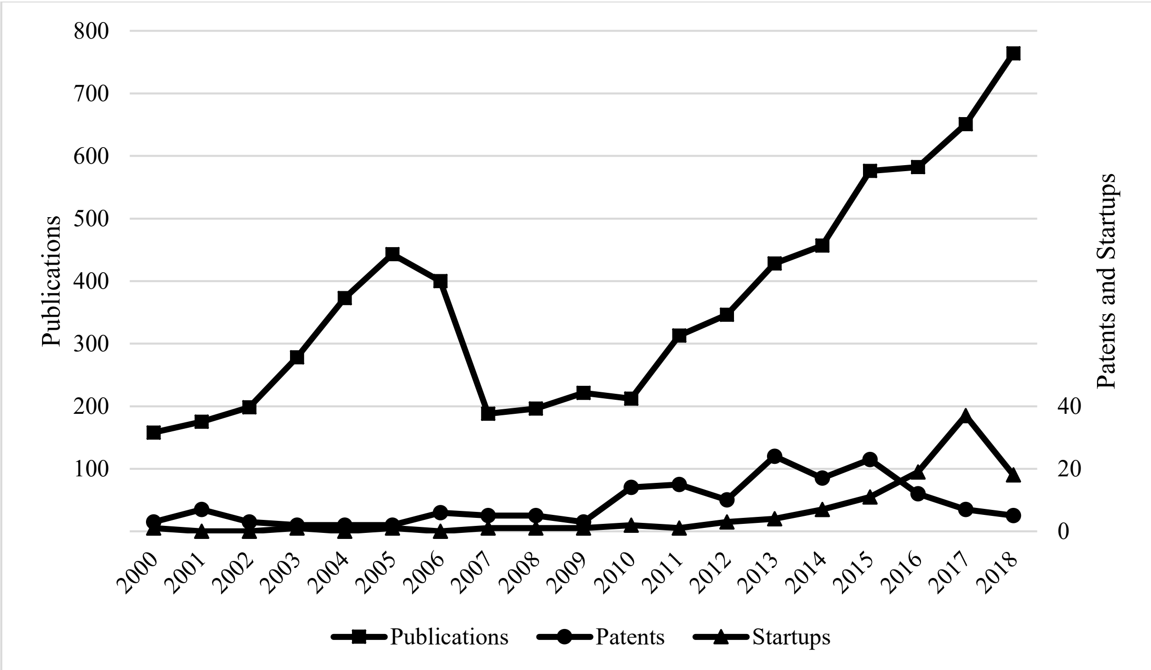

Figure 5: Number of AI-related publications/patents/startup formations over time

Given the low number of identified patents in Sydney and the practice of filing different version of the same patent, the increase in number between 2012 and 2015 and the subsequent decline could be misleading.

The number of startups founded however, shows a clear increase starting from 2012 with a spike in 2017. This increase happens with a temporal delay compared the rise in publication output.

6 DICUSSION AND SUGGESTIONS FOR FUTURE RESEARCH

Because EEs are a critical part of economic growth and sustainability (Thurik et al., 2013; Weill & Woerner, 2018; World Economic Forum, 2013), any improvement in understanding their dynamics and increasing their effectiveness could bring many benefits to many regional economies, including those of cities. One such improvement might develop from an understanding of the dynamics of knowledge spillovers based on details of the assessment of knowledge bases of a specific technology within an EE, which is the topic of this paper.

Although the entrepreneurship literature promotes the creation of a competitive environment for flourishing EEs that tap into the opportunities generated by digital technologies, few studies investigate knowledge spillovers on the ecosystem level (Acs et al., 2009; Goel & Saunoris, 2017), and even fewer focus on knowledge bases that generate these knowledge spillovers (Qian, 2018). Our study proposes an approach to the assessment of the dynamics of knowledge bases for a specific technology with patents, publications, and startups as key metrics.

This study presents an illustration of this assessment approach, examining the evolution of AI patents, publications, and startups in Sydney. In this way, rich observations at the city level are used to understand the dynamics of AI knowledge spillovers in Sydney's EE. Overall, observations indicate that knowledge spillovers among knowledge bases of AI are low. The rather strong publication record compared to the rather weak patent performance seems to confirm Sydney's reputation as being a strong research location with a few world-leading universities, but not necessarily a pioneer in realizing knowledge through generating intellectual property. This finding seems to align with the fact that as a country, Australia ranks lowest across all OECD nations for collaboration on innovation between business and research institutions (OECD, 2017). Interestingly enough, our study also shows how local emerging knowledge has a great deal of international collaborations, but how this does not turn into local realized knowledge in the form of patents owned by these collaborators. This is one of the threats of EEs mentioned in literature where knowledge spillovers might reverse to the disadvantage of a region (Audretsch & Belitski, 2018). Finally, the growth of experimental knowledge base shows some parallel to the growth in emerging knowledge but the size of experimental knowledge base is so small that it is not easy to argue a spillover taking place among them. This might be due to time lag as observed in some studies (Goel & Saunoris, 2017), but our study examines a period of 19 year and it does not show a clear time effect. These findings clearly confirm our goal of expounding nuanced observations on the dynamics of a technology domain in an ecosystem by deconstructing it into three knowledge bases.

Theoretical Implications

We extend techniques outlined in the literature in two novel ways. First, we assess the technical knowledge base of an EE using both traditional metrics of patents and publications and entrepreneurial firms established in a specific technology field as discussed in a number of studies (Lindholm-Dahlstrand et al., 2019;). The addition of startups as a metric for quantifying experimental knowledge generation allows this paper to develop an assessment of a technology's knowledge base with three pillars, called realized, emerging, and experimental knowledge here. As argued in knowledge-spillover-based strategic entrepreneurship (Ferreira et al., 2017), our study identifies the strategic role of entrepreneurs in knowledge spillovers within EEs and advances thinking about specialization within a specific technology domain and its economic implementations. Further, our assessment might offer a rich input for any strategy maker, either entrepreneurs, policy makers or managers of institutions such as banks within an EE that are interested in taking deliberate action to utilize knowledge generated within ecosystem.

Second, we offer a longitudinal exploration of the AI knowledge base in Sydney's entrepreneurial ecosystem. Our findings demonstrate the dynamic nature of the assessment approach that identified the key actors, major networks, and critical know-how in the local knowledge base of AI over a 19-year period. Similar to the finding of Spiegel (2017) where multiple configurations of city attributes might generate the existence of separate EEs, our study enables an understanding of how the diversity of knowledge bases of a specific technology in an EE might generate diverse knowledge spillover behavior. . In addition, as argued in Alvedalen, and Boschma (2017), a longitudinal exploration could enrich the observation of networks within an EE.

Practical Implications

A systemic understanding of the knowledge bases in a city/region could indicate how best to align existing technological opportunities with entrepreneurial capabilities in local ecosystems as the knowledge-spillover-based strategic entrepreneurship theory suggests (Ferreira et al., 2017). For example, the collection of rich local data could prevent decision makers from following unrealistic trends propagated through global hype in relation to technologies such as blockchain as discussed in section 4. We believe that a closely connected analysis of individual technologies in an EE could significantly aid managers and entrepreneurs to improve their utilization of technologies by understanding the knowledge bases available in the region and provide ecosystem stakeholders awareness of the gaps and opportunities in the ecosystem that could lead them to proactively seek out means of collaboration, resulting in increased knowledge spillover. Thus, the assessment approach supplies a tool for strategy and innovation (Helfat & Raubitschek, 2018; Spiegel, 2017).

Limitations and Directions for Future Research

The study has three major limitations that could prompt future research. First, the literature does not offer any clear definition boundaries on AI, thus we used WoS and ICL categories in our study even though this might lead to noise in the dataset. Second, it narrows its observations to one technology, namely AI, omitting the knowledge synergies that might occur between AI and other technologies (Cockburn et al., 2019). Other knowledge bases might be grounded in other subcategories of digital technology or other technologies, such as those of manufacturing. This could be an interesting follow-up topic for researchers looking to expand the categories of technologies and to determine metrics that could assess the role of these kinds of synergies in knowledge spillovers (Motohashi, 2018). Third, we limit our focus to startups as sources of experimental knowledge. Future studies might expand this to cover other areas where experimental knowledge builds up, such as in university spinoff companies (Miller et al., 2016) and acquisitions, (Lindholm-Dahlstrand et al., 2019). Third, this study is limited to one city (Sydney) and one technology (AI), making its results difficult to generalize. It would be desirable for future studies to consider whether empirical work could be conducted with multiple cities and/or multiple technologies. Other cities to study might equally be found in Australia or elsewhere because regional differences may be as important as international ones, as shown by Kriz et al. (2016) for the Australian case.

Finally, we draw researchers' attention to three additional topics as interesting research avenues. This study focuses on AI alone among digital technologies, but it may be that multiple ecosystems with different entrepreneurial opportunities might coexist in different subcategories of digital technologies, whether 3D, robotics, or other general purpose technologies, such as biotechnology or nanotechnology (Startup Genome, 2019). We hope that this line of thinking could inspire future studies to investigate the emergence and existence of multiple EEs. Similarly, this study has clearly shown that even though EEs are embedded on a geographical location, it has strong linkages into international networks as Sydney's case highlights. That is why future studies could integrate internationalization theories further in examining the roles of local and international ties at each knowledge base categories (Groth et al., 2015). Another interesting topic for future studies might be to accommodate the differences among knowledge actors such as universities in terms of their impact on knowledge spillovers in order to capture the interactions among actors and knowledge bases of an EE (Rodriguez-Gulias et al., 2017).

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