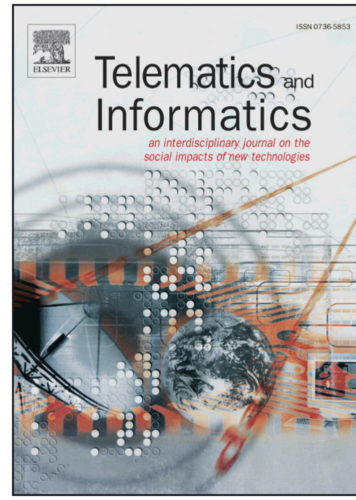

Technology convergence in the Internet of Things (IoT) startup ecosystem: A network analysis

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Technology convergence in the Internet of Things (IoT) startup ecosystem: A network analysis

Sangmin Lim[1], Ohsung Kwon[1], Duk Hee Lee[1,*]

Abstract

The role of investors in the growth of startups has been continuously studied. Our paper complements this stream of research by adding a new role of the investor in the Internet of Things (IoT) field, as a channel of knowledge sharing among startups. The relationship between "Internet of Things" startups located in the US and its investors leads to technology convergence as a result of knowledge sharing from investors. Using network analysis and a co-occurrence method, we find that investors in the IoT field play an intermediate role connecting startups by forming an ideal topology for knowledge sharing among them in the IoT industry. IoT startups having investors and more connections to other startups show greater technology convergence. Based on the above findings, this study argues that technology convergence occurs in the venture network as a result of investors playing the role of a channel of knowledge flow.

Keywords: Internet of Things; Technology convergence; Investors; Network analysis; Knowledge flow

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Abstract

Since the occurrence of the concept of "Internet of Things (IoT)", startups have been actively joining the IoT industry creating new products and services by converging existing technologies with the internet. This paper conducts a network analysis on the IoT startup ecosystem in order to see how the ecosystem is constructed and also see how and what technologies are transferred among startups. With a sample of US based IoT startups and investors, our main findings show that the investors in the IoT field play an intermediate role in knowledge sharing by connecting startups and forming and ideal topology for technology convergence. Under this stream, IoT startups having investors with more connections to other startups show greater technology convergence and also can be divided as technology giving or absorbing groups within the startup ecosystem. Based on the above findings, this study argues that technology convergence occurs in the IoT startup network as a result of investors playing the role of a channel of knowledge flow.

Keywords: Internet of Things; Technology convergence; Investors; Network analysis; Knowledge flow

1. Introduction

Around a decade ago, a new concept of technology was introduced in our lives which aimed to converge all “Things” via Radio Frequency Identification (RFID), Internet, sensors and tags creating a paradigm where all things were able to communicate among each other called the “Internet of Things (IoT)”. The use of this concept was first limited to the macro level focusing on convenient and efficient productions in factories and sites, but has now evolved into a concept that takes place frequently in our daily lives in forms of various technologies.

This new concept has been growing dramatically since its release, and is predicted by prior studies and reports to continue its growth in size and numbers more rapidly(Shin, 2014). Reports on IoT by Gartner (2017) show that approximately 8.4 billion IoT devices are in use in 2017 and will reach 20.4 billion by 2020 almost doubling in numbers. Reports made by the international data corporation (IDC) also show the rapid growth of IoT. In 2017, $800 billion was invested in the IoT industry and the investment amount is also expected to increase to $1.4 trillion by 2021 as firms and organizations are planning to continuously invest in IoT related fields (IDC, 2017).

With IoT gaining momentum across the world, startups have also been actively taking part in the IoT industry. According to a report studying the North America based startups in the IoT field, $125 billion was invested to 2,888 startups in 2017. The value of these startups grew to $613 billion, and produced 95 startups that are now worth a billion dollars so called unicorns (Koetsier, 2017). In proportion with the explosive growth of IoT startup firms, new technologies have also been created by startups under the IoT concept. As past studies show the underlying value of IoT to be creating new technologies through the convergence of the existing ones (Atzori et al., 2010) startups have and are creating new technology by converging the “Internet” and “Things” as the literal definition of IoT is the combination of the internet and other objects. Many startups including ones such as Ring and Actility have produced products and services that have great influence in our lives by merging traditional knowledge with the internet to create new ones (Gubbi et al., 2013). As new products and services created by startups in the IoT field continue to grow as well as the importance of the converged technology, yet, academic research on the knowledge flow among startups is still in a very nascent state. The majority of studies on knowledge flow among industries and firms focus on the collaboration of firms and research institutes (Håkansson, 1990; Leydesdorff, 2009; Leydesdorff and Etzkowitz, 1996), patent citation (Guan and Chen, 2012; Ma and Lee, 2008), merger and acquisition (Bresman et al., 1999; Yang et al., 2008) to be channels of knowledge flow, however does not focus on this process understanding the features of startups nor offer an accurate analysis based on in the IoT industry. Therefore, in order to fill the gaps in research, this study focuses on the process of technology convergence among startups within the IoT industry, to identify the types and channels of knowledge flow.

To meet the needs of such research, this paper contributes to the IoT field by analyzing the IoT startup industry as well as finding how knowledge is transferred among IoT startups accordingly focusing on the characteristics of startups. By reexamining the roles of investors in the network, we draw upon the investor to be the mediator to connect startups and play the role of conduits of knowledge among the startups as prior studies prove that funding through investors not only provides financial support but also technology and information (Brown and Butler, 1995). We believe that investment in startups is the channel of knowledge diffusion and eventually can be utilized for technological convergence. As investors play a role as mediators among several venture startups, knowledge and technology are passed on through them from one firm to another. Based on this background, this paper includes (1) analyzing the investment network between investors and IoT startups, (2) transforming the two-mode (investor–startup) network to a one-mode (startup–startup) network to analyze the network topology for the flow of knowledge, (3) revealing the convergence of technology through keyword analysis, and (4) providing evidence of investor’s contribution to the convergence of technology as intermediaries of knowledge flow, and finally (5) empirically examine the types of technology converged in the IoT startup ecosystem.

2. Literature review

2.1 Definition of IoT and technology convergence

The concept of a network connected device was first presented in 1990, when John Romkey created a toaster that was connected to the internet so it could be turned on and off remotely to toast bread at a conference. This rather simple device was a great sensation at the 1989 Interop, and was acknowledged as the first steps of the IoT (Romkey, 2017). Even before Romkey, there were efforts of network connected devices such as a modified vender machine at Carnegie Mellon university which was able to transfer information on its inventory and even if the drinks were cold or not via the internet. Despite efforts to connect objects and the internet, the concept of IoT started to gain momentum and became famous due to the concept that the Auto-ID center at MIT proposed. The MIT Auto-ID Center proposed the concept of IoT to be “All objects equipped with identifiers such as RFID, barcodes, QR codes and digital watermarks allowing computers to manage and store them” opening a new era for the IoT. Since, efforts to connect everything, everywhere has continued, focusing on the development and integration of IoT technologies and resources.

With the advancement of IoT technology, applications in various fields using such technologies has followed. IoT technologies are applied in multiple areas such as smart home, manufacturing, agriculture, building and home automation, medical and health care and has a potential to be used in many more fields. Applications such as the smart home system is already deeply in our daily lives changing the way of living. IoT devices can be utilized by a main hub or controller such as a smartphone to provide users with a central control for household devices. Lighting, heating and home security systems can be controlled remotely as well as televisions and media devices (Kang et al., 2017).

Smart home applications are now evolving to become more sophisticated. By merging the voice recognition technology to IoT devices, IoT devices can be voice controlled and also perform various functions such as ordering products or receiving customized news over the speaker making life easier at home by enhancing multi-tasking abilities and easing the usability of products (Meola, 2016). Another example of technology convergence could be applications in the energy management section. By integrating sensors into all forms of energy consuming devices, the optimization of energy consumption is possible by effective power generation and energy usage (Parello et al., 2014). By remotely controlling all energy devices and also scheduling energy usage, effective usage of energy is advanced due to the integration of IoT technology (Ersue et al., 2015). The integration and convergence has brought a greater value in various sections to customers and the society (Arruda Filho and Brito, 2017). IoT technology is a catalyst combining different technologies from various fields creating new ones and is expected to bring great value to the users and also function as a the key pillar of the upcoming 4th industrial revolution by such products and services contributing to other emerging fields.

2.2 Startups and the ecosystem

Startup companies are defined to be a fast growing, entrepreneurial venture which aims to meet the needs of a marketplace with an innovative product, process service (Katila et al., 2012). Research on startups find that new ventures create more innovations and more innovative products than traditional large, incumbent firms (Song et al., 2010). Startups being small in size have virtues as quick decision making and easily changing strategies and plans to suit the market (Hellmann and Puri, 2002). However, startups rarely have the sources to carry out their innovative ideas (Shane, 2009). Most of the cases, startups lack financial resources, which leads to the absence of man power, equipment and market search for product and service launching. (Hurst and Lusardi, 2004). In order to complement the needs of startups, investors have played a critical role to support the startups creating an investor-investee relationship that can easily be portrayed as a network. Studies find this investor-investee network to be reflected as a startup ecosystem, as each player is linked among each other through various connections (Motoyama and Knowlton, 2017). Startups and investors as nodes can be connected with each other through various links as investors offer financial, emotional and technological support to the startups (Deeds et al., 1997; Shane and Cable, 2002), and startups give shares and profit in return. Recently, new types of investments have appeared as the methods and form of investments have evolved making involvement in startups a more general and easy such as crowdfunding and online investment platforms. Due to these changes and the importance of startups, investing in startups with potential to be innovative is an important economic and social phenomenon. With more participation from diverse players, the ecosystem grows and benefits the startups through various supports from the connections of the network (Hallen, 2008). Prior studies show that entrepreneurial networks serve as societies to share ideas and knowledge for entrepreneurs' growth of potential abilities (Birley, 1985; Smeltzer et al., 1991).

2.3 Investors as intermediaries of knowledge flow in the network

As knowledge transferring is important to a firm's success, throughout the various supports offered by investors, the importance of knowledge and technology transferring is found to be critical. As knowledge is particularly shaped into the form of technology by patents and products (Acs et al., 2002), studies found that technology from different industries come together, creating new technologies through convergence (Choe et al., 2016; Kim et al., 2015). With technology flow presenting a new type of knowledge sharing, firms are able to adapt this new knowledge to their strategy or products (Audretsch and Keilbach, 2004) and find insights regarding services and features that could be noticed in the markets (Cohen and Levinthal, 1994). The importance of knowledge obtaining is increased in small firms, as it is found that startups in general greatly depend on the usage of existing knowledge as well (Shane, 2001).

Investors, offering know-how and information to startups in order to foster better alliances and innovation output (Brown and Butler, 1995) also work as conduits of knowledge transferring as well. Studies show that the information provided by investors at early stages of startups serves as a solution to reduce the uncertainty of technology development (Elitzur and Gavious, 2003) and as a base for further development. Specifically, venture capitalists are found to play the role of linking knowledge in the startup ecosystem (Hoang and Antoncic, 2003) and also serve as information intermediaries, offering the appropriate resources and access to information to venture startups (Gans et al., 2002). Startups, who gain most from opportunities created by new markets, are necessarily found to be the prime beneficiaries of knowledge from different sectors, (Audretsch and Keilbach, 2004) which makes the role of investors as knowledge conduits more important.

In this context, as information and technology are transferred to startups through venture capitalists, investment links can operate as channels for knowledge spillover, eventually leading to the convergence of technology among startups. In this paper, by analyzing the investor-investee network, we focus on how technology is converged through investment links in the IoT startup ecosystem, and also examine if more technology is converged due to the topology of the investor and investees.

3. Data and methodology

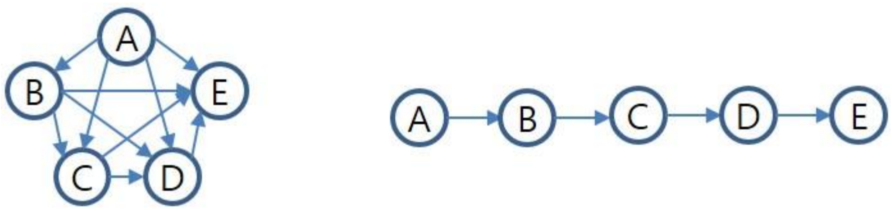
We use investment data accumulated from CrunchBase.com, an investment platform for venture startups, venture capitalists, and individual angel investors. CrunchBase provides information on the investors such as the location, size, main investments, amount and round of investments. Information on the startup firms contain the location, size, team member, main technology and products and also the amount and round of investment received. Startups are defined as IoT startups if the startup has keywords such as “Internet of Things” or “IoT” in the firm categorization criteria. From all the data available, we select those IoT startups that have been funded more than once by an investor located in the United States. Consequently, our dataset consists of the 843 firms that were funded between 1998–2016 by 1,068 investors. Although investments were made in several stages, we focus only on the very first round of investments because studies emphasize that investments by venture capitalists tend to focus on the initial stages (Dutta and Folta, 2016) and the knowledge transfer effect is maximized at the initial stages (Stuart et al., 1999).

3.1 Network analysis

Network analysis is used in various fields, such as economics and business (De Benedictis and Tajoli, 2011; Horton et al., 2012; Kim et al., 2014; Kwon et al., 2017), to reveal the relationship among actors through nodes and links. Each node(investors, startups) is connected to others through links(investment activities), which defines the relationship among the entities. By such analysis, it is possible to capture the positions and roles of each node in the network and also reveal the topology of the network itself.

First, to analyze the structure of the IoT startup ecosystem, we construct the network of IoT ventures and investors graphically. The network is formed in two different ways: one is a two-mode network among startups and investors, and the other is a one-mode network among the startup firms only. Fundamentally, the investments are indicated by the links in the network. First, in the two-mode network, links are generated between an investor and a startup through investments, but not homogeneously. Through this process, it is possible to identify the startup that has the maximum investment or the investors that are the most active in the network, thus indicating their importance and position within the network.

The one-mode network of startups is formed by a one-mode projection of the two-mode network. The one-mode projection starts by selecting one node type and linking the nodes as if they were connected to a common node of the other type at least once. For example, in this paper, links between two startups have a direction that starts from the startup that has been invested in earlier heading to the startup that has been invested in later. If an investor has invested in startups A, B, C, and D sequentially, then investor to A, investor to B, investor to C, and investor to D links are generated for the two-mode network and A to B, B to C, and C to D links are formed for the one-mode network. To ensure robustness, we make the networks in two other ways. One network is formed such that the startups are serially in a line in the order of investments. The other network is in the shape of a type of "clique," which means that all nodes are connected to each other. Actually, startup A is a precedent firm of startups C and D as well as startup B. Thus, in the second network, the links are A to B, A to C, A to D, B to C, B to D, and C to D among the startups. Further, we analyze the characteristics and properties of these networks. The conversion of the two-mode network to a one-mode network can show the mutual connections among nodes that are not directly connected.



<Fig. 1> Graphical view of clique and serial modes of network

Next, we determine the important firms in the one-mode network with respect to connectivity and the role of transfer of effective knowledge. Following the criteria of generated links, startups invested earlier usually have more in-degree centrality and startups invested later have more out-degree centrality. To normalize the value of the degree centrality, we select the outflow-inflow(O-I) index for categorizing the firms in the sample (Choe et al., 2016). The O-I index facilitates the categorization of firms in two groups, firms funded early and firms funded late, using the difference between the out-degree and the in-degree centralities. The precise formula for calculating the O-I index is as follows:

$$\mathrm{O-I\ index} = \frac{\text{Outdegree centrality} - \text{Indegree centrality}}{\text{Outdegree centrality} + \text{Indegree centrality}}$$

The range of the O-I index is from -1 to 1. A startup plays a “spillover” role if the value of its I-O index is close to 1; on the other hand, it performs an “absorbing” role if the value is close to -1. However, as Choe et al. (2016) mentioned, the O-I index is not sufficient for classifying the representative startups in the entire network because the degree centrality considers only the neighborhood of individual startups. Another network property should be used to reflect the characteristics of the entire network, and thus, we use the betweenness centrality, which is a measure of the role of a bridge or broker within a network. This implies that a startup that has high betweenness centrality can transmit or absorb technological knowledge through a homogenous investment. The formula for calculating betweenness centrality is as follows:

$$\text{Betweenness centrality} = \frac{\sum_{j \neq k} g_{jk}(i)/g_{jk}}{(n-2)(n-1)/2}$$

where n is the number of startups in the network and $g_{jk}(i)$ is the number of geodesics via startup i among other startups j and k. We categorize the startups in four groups based on (1) high O-I index and high betweenness centrality, (2) low O-I index and high betweenness centrality, (3) high O-I index and low betweenness centrality, and (4) low O-I index and low betweenness centrality. More specifically, we are interested in groups (1) and (2), which can play important roles in the network.

3.2 Keyword analysis

Startup firms in the IoT industry that are listed in the dataset each select two or more keywords, which describe the technology that is in use at the firms. Keywords such as “Internet,” “Wireless,” and “Android” are some keywords firms select to describe the identity of their firm or service. By mining such information, we can use keywords to identify the technology that the startups possess. Because we assume that startups share or transfer knowledge and technological know-how through investors, keywords that represent the key technology of the startups are shared among the startups funded by the same investor considering that the knowledge stock is accumulated and shared from and by the investor. To see the pattern of such technology convergence due to knowledge spilling, we perform co-occurrence-based analysis, which is widely used in text-mining keyword analysis (Kim et al., 2015; Netzer et al., 2012; Pang and Lee, 2008).

The basic assumption of the co-occurrence-based analysis is that if two or more keywords occur a sufficient number of times, startups are more likely to choose such a combination of keywords because they are interrelated. Thus, by analyzing the simultaneous appearance of the combination of keywords in pairs, it is possible to identify the original and emerging patterns of keywords. When applying the co-occurrence-based analysis, it is likely that there could be overlapped keywords if the firms are related with each other. There is a higher possibility of an overlapped keyword if the firms have similar characteristics or perhaps are in the similar market. If the same keyword is overlapped among firms with the same investor, it can be assumed that knowledge has been transmitted from the former firm to the later. The occurrence of a new technology can be revealed by comparing the keywords of the former and later invested firm to see if a new keyword was generated. To extend our findings, the purpose of our study is to not only find the occurrence of keywords but to demonstrate technological convergence Thus, we compare the combinations of two keywords between a startups funded earlier and startups funded later, that is, a pairwise analysis based on the co-occurrence analysis. If a combination of two keywords exists in the startup funded later, but not in the startup funded earlier, the combination suggests a new "technology." For instance, two startups that received funding earlier have keywords (A, B, C) and (C, D, E), respectively. Then, their possible combinations are A-B, A-C, and B-C for the first startup and C-D, C-E and D-E for the second startup. Further, consider two startups that received funding later, which combinations (A, D, F), and (B, D, E). Thus, there exist combinations A-D, A-F, and D-F, and B-D, B-E, and D-E, respectively. The keyword "F" is a new emergent; thus, A-F and D-F are new emergent combinations. The A-D combination, even if both "A" and "D" exist in the startups funded earlier, is a new emergent because the combination does not exist in the startups funded earlier. B-D and B-E are same as A-D, and D-E is the only existing keyword combination. Finally, we calculate the proportion of the new combinations, that is, 5/6 (83.3%) in this case. To ensure a sufficient sample size, we choose the period from the first half of 2012 to the first half of 2016 and a rolling approach. We set the rolling window size as one year and the interval as half a year. Investors that have many links with startups are chosen as the sample, and the results of the top two, top five, top 11 and top 28 venture capitals are presented. The top 28 investors with the maximum links comprise only venture capitalists with a huge difference in the number of links compared to that of angel investors. The top two, top five, top 11, and top 28 venture capitalists are divided because the first two groups hold 15 links each, followed by the group of top five, which holds nine to 11 links. An average of five links exist for the investors starting from the top 11 venture capitalists to the top 28 venture capitalists, showing a firm difference in the number of links possessed. The major two venture capitalists were 0.25% out of the total investors but invested 2.8% of the total investments. The next three large venture capitals were 0.37% out of the total investors and made 2.7% of investments out of the total investments. The following six venture capitals were 0.74%, and 3.46% each in the portion of investors and investment each. Meanwhile groups with only three links were 3.1% out of the total investors and had 7.85% of the total investment links. Groups with less links showed to have a larger portion of investors, but relatively a lower portion of investments. In cumulative status, the top 28 venture capitals were only 3.4% out of the entire number of investors but made 15.7% of the investments, while the remaining groups added up to be 96.6%, predominating the portion of investors had a lower 84.3% out of the total investments.

4. Results

4.1 Network analysis of the startup-investor network

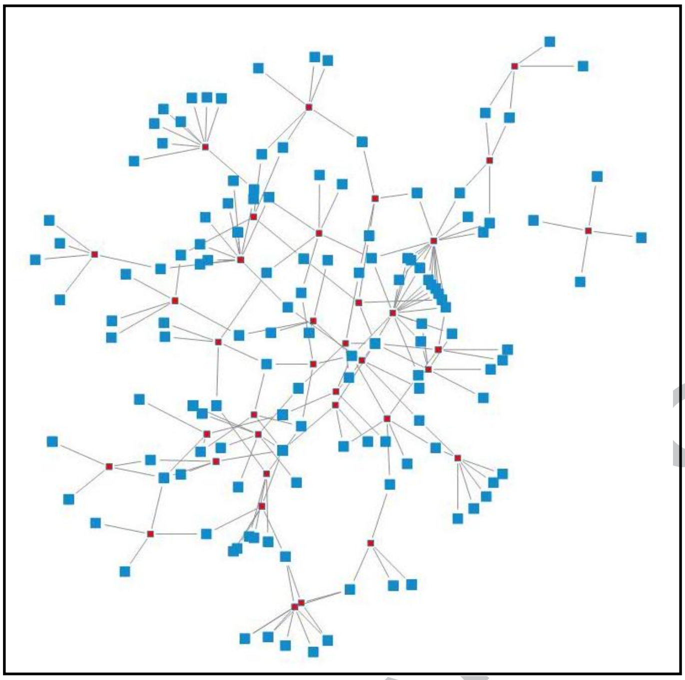
The entire network including all startups and investors comprise one main component and several satellite networks. The main component in the IoT network contains around 85% of all the nodes and links and is interconnected mostly by major venture capitalists.

Fig. 1 shows the center of the two-mode network among the venture capitalists and the investor-backed startups with a cutoff. The red circle nodes denote the investors and the blue square nodes denote the startups.[2] To avoid complications, we set the cutoff value as four connected links of investors. According to Fig. 1, the main component of the IoT network is fully connected among investors and startups. Even after the single or low value links are deleted, the component still remains as a whole network with only one isolated component. If

[2] It is the subnetwork of the sample, but not the entire network.

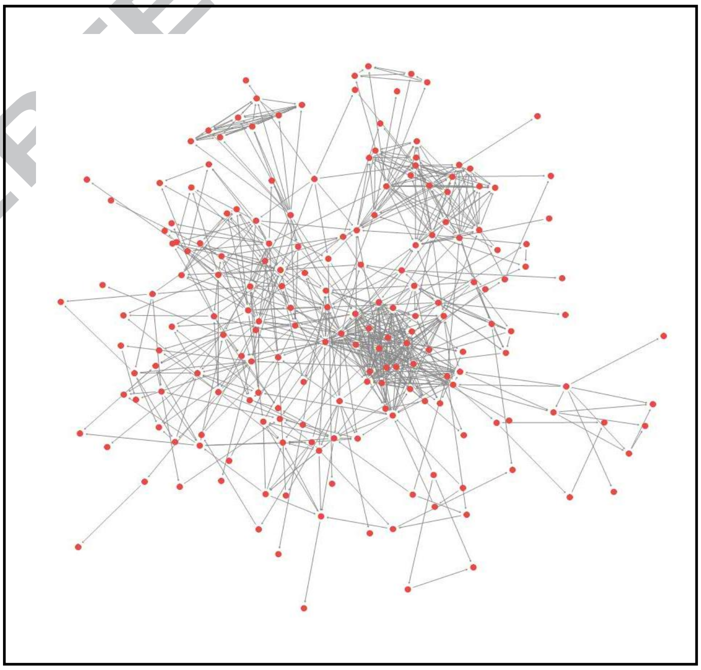
we apply this network to the real world, we see that because startup companies, in a way, compete with each other, a source of connection among them is not feasible to apply. However, with investors playing the role of an intermediate node, via such investors, the startup network now shows an attractive topology to share or perhaps transmit social capital or knowledge among startups. Through the role of investors, the network shows a topology where the knowledge of randomly selected startups can reach any other startup within the network through investment links because the network is fully connected. Within such networks, investors are placed as intermediaries as they play the role of connecting startups to different sources of need. Due to the information provided by such networks, more opportunities of strategic alliances are created (Lindsey, 2008). Such strategic alliances are more favorable for the growth of startups. Alliances among firms and connections are found to create knowledge spillovers, which foster innovation and bring about collaboration among the main entities in the startup ecosystem and result in higher efficiency and progress owing to knowledge sharing (Inkpen and Tsang, 2005; Mowery et al., 1996; Waltera et al., 2007)

Due to practical limitations, knowledge transmission may not be feasible for more than one or two stages of connection. However, this network can show that due to network topology, knowledge can flow from one end to another through investment channels. Thus, with investors as a connecting bridge, a feasible structure for sharing knowledge and information among the seemingly unrelated firms is found. The isolated components are mostly formed by individual angel investors given that they show a different topology in the network. Because most angel investors have prior experience as members of startups, they tend to have a deep understanding about the field they are investing in (Van Osnabrugge, 2000), which can lead to a different approach in investing.



<Fig. 1> The two-mode network of investors and startups

Fig. 2 displays the one-mode network among startups in the serial mode. The radius of the nodes is proportional to the degree centrality they possess. Because the one-mode network is projected serially, the network can show the transmission of knowledge from one startup to another with directions. Considering the serial mode, we can assume that startups that were funded at an earlier period will transfer knowledge to those that were funded later. Similar to the structure of Fig. 1, many startups are connected to each other, thus providing an adequate structure for knowledge to flow from one node to another. Most of the startups within the network show characteristics of a knowledge spillover startup or a knowledge absorbing startup. In addition, they generate their own clusters homogenously and share allied knowledge due to the same investor connecting them together at a short distance. Startups invested in by the same investors seem to neighbor each other more closely compared to other startups that have been invested in by other investors. Because some venture capitalists play the role of a bridge, startups related to the same venture capitalists seem to form a cluster in the network. This could further be enhanced and interpreted as the syndication among startups due to the same investment source. Because venture capitalists show more diverse connections compared to individual investors, they tend to form a syndication for joint investment and information sharing for better selection and valuation (Brander et al., 2002). Throughout syndication deals, venture capitalists are able to share risk, broadening their areas of funding through complementary networks, and develop reciprocal relationships for the exchange of information and knowledge (Hochberg et al., 2015; Hochberg et al., 2007; Sorenson and Stuart, 2001; Sorenson and Stuart, 2008). By broadening their network and role within the network, investors can benefit within their own network as gatekeepers or information transmitters. According to Zhang et al. (2016), venture capitalists tend to syndicate more with other venture capitalists having expertise in diverse fields for attaining a broader network.



<Fig. 2> The one-mode projected network of startups (cutoff value 4 of the venture capitalists)

4.2 Keyword analysis

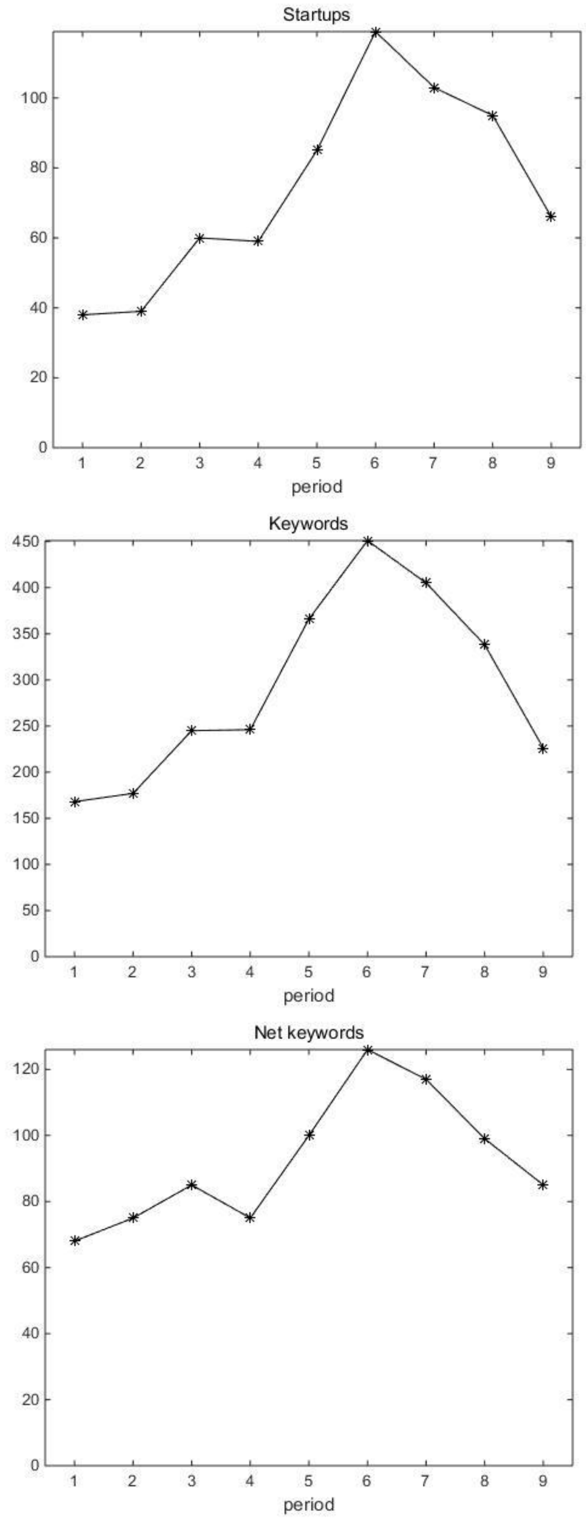
Fig. 3 shows the number of startups, their keywords, and net keywords, which refers to the exclusion of duplicated keywords. The IoT entrepreneurial market has been emerging in periods 1–6, that is, from the first half of 2012 to the second half of 2014. Period 6 has a total of 119 startups funded at the initial stage, and period 7 has 103 startups being funded, showing the very peak of IoT startups. The number of keywords and net keywords also follow this increase during the same period, showing a maximum of 451 keywords and 126 net keywords. After the peak, the entrepreneurial environment of IoT seems to mature, showing a slow decrease in initial funding and occurrence of net keywords.

To explain technology convergence with the combination of keywords, the trend for new emergence is shown in Fig. 4, which displays the proportion of new emergent combinations of keywords of the startups funded later. From the starting period, the top two and top five venture capitalists (the sum of the top two venture capitalists and the next three venture capitalists) make more new keyword combinations than the top 11 and top 28 venture capitalists. Startups that are funded by the top two major venture capitalists show a higher ratio of the creation of new technology of approximately 72% compared to 20% of that of the firms funded by the top 28 venture capitalists. One reason for the gap could be explained by the link numbers that each venture capitalist holds. Because top venture capitalists possess more links, which means more connections with numerous startups in the prior period, it could also mean more technology stock to pass on to the firms funded by them later. This logic can be proved from Fig. 4, which shows that with more connections, more knowledge can be gathered and passed on to the investees.

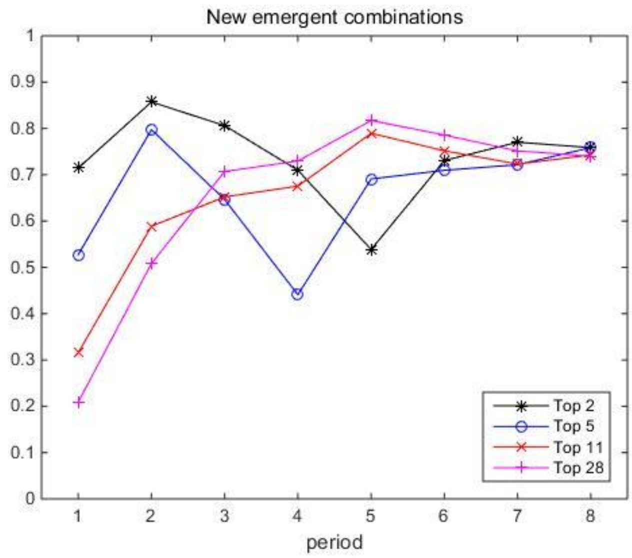
Firms that have been funded can create new technology by combining separate technologies from firms that have been funded earlier by the same investors. However, the convergence ratio drops for the top two and top five venture capitalists in periods 4 and 5, while the ratio for the top 11 and 28 venture capitalists grows during the same periods. Results are plausible that the first-tier venture capitalists, who play a leading role in startup investment, make more technological convergence, specifically in the emerging period. The major drop in the top two venture capitalists can be interpreted in various ways. However, with further investigation, the top two investors invested heavily in other startups in different fields at the certain period due to a momentum. This fall also effected the cumulative ratio of the top five venture capitals to fall as well. Except for the two periods, continuous investment in the IoT ecosystem continues.

The importance of secondary venture capitalists also increases over time, indicating that secondary venture capitalists also pass on their technology for more convergence rather than relying on links or size of capital. Such phenomena can occur due to the movement of human resources among firms, given that the role of investors also involves attracting human resources. Perhaps, such technology can be passed on through the use of patents or technology meetings because initial investors have a large proportion of ownership in early stage startups. As the market matures, the creation of new keywords and combinations continue to grow not only by influence of first-tier investors but also second-tier investors. Finally, all venture capitalists can cause some technological convergence among startups and their industry by investing in them during mature periods and transferring knowledge to other startups they fund.

Investors with single or small amount of links were also examined in this measure. The majority of the total investments were one-time single investments which were not able to form a network as there was only one investor and one startup. Investors with two links also showed a very low and discrete convergence ratio as the number of links were limited. In other words, not much knowledge was received nor passed on among startups within the ecosystem.



<Fig. 3> (a) Number of firms, (b) keywords, and (c) net keywords



<Fig. 4> Proportions of new emergent combinations

4.3 O-I index analysis

Fig. 5 and Fig. 6 each show the O-I index and betweenness centrality graph of serial and clique network models, respectively. The figures are derived from the O-I index and the betweenness centrality for each axle. Betweenness centrality is a parameter that measures the activeness of nodes. Even if a node holds a high in- or out-degree, if the node is not active within the network, the meaning of such analysis could fade away. Therefore, nodes with low or no betweenness centrality are not included in a group. We define the “spillover group” as startups that have a positive O-I index (more out-degree) with high betweenness centrality and the “absorbing group” as startups that have a negative O-I index (more in-degree) with high betweenness centrality.

Through the O-I index, it becomes clear that knowledge flow has a direction. Nodes with a higher out-degree denote that they are passing on their knowledge and are therefore, defined as a spillover group, and nodes with a higher in-degree denote that they are receiving more links from other startups compared to other nodes, which can be interpreted as absorbing knowledge.

Through such analysis, we can focus on the characteristic of each firm and the role it plays either as a "giver" or "absorber." Because nodes funded earlier develop their technology or knowledge stock through investments, this knowledge can be passed on to the same "allied" startups through the same investor. Firms with key technologies at early stages that act as "giving nodes" can perhaps benefit by using these technologies or have no choice but to share their knowledge.

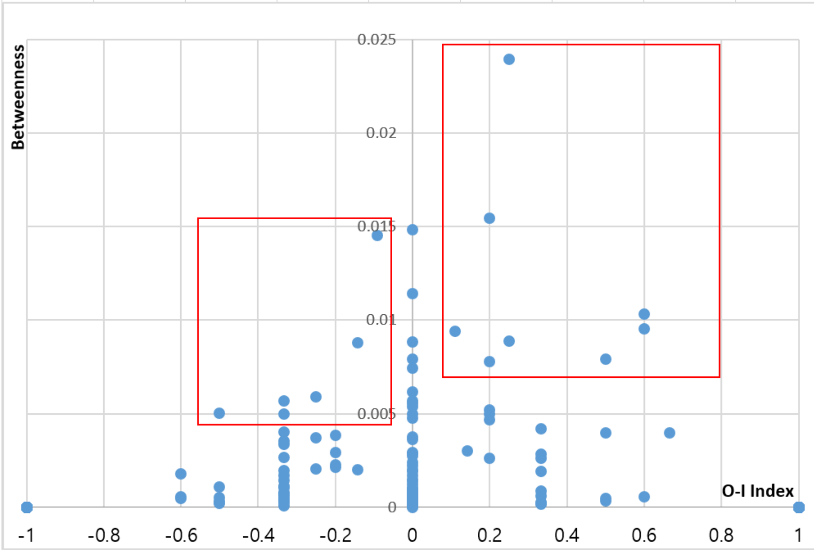
From Tables 1 and 2, we analyze the worthwhile startups that have belonged to both the groups at least once. In general, according to Tables 1 and 2, it is likely that spillover firms are usually the sources of technological knowledge and pioneers of their fields. On the other hand, most of the absorbing firms are consumer-friendly businesses that try to employ the applied IoT technologies. There are dissimilar category keywords between the two groups. The main keywords of the spillover startups appear as "Wireless," "Home Automation," "Internet," "Finance," and "Big Data," which have wide coverage and are generally defined as fundamental technology. The absorbing startups have keywords such as "Consumer Electronics," "Health Care," and "Home Automation," which are familiar in the daily life of consumers and are a result of convergence with various technologies.[3] Moreover, the keywords of absorbing firms, in particular, are "Art," "Android," "iOS," "Parenting," "Apps," and "Developer Tools," while spillover firms have keywords such as "Manufacturing," "Semiconductor," "Telecommunications," and "Industrial." Such trends can be interpreted as follows: knowledge emerges from the sourced technology, specifically in IoT and flows to the sub-discipline and converged technologies to combine with other knowledge through the connected network. Startups that were funded at early stages might be selected due to the

[3] The general words, such as "Internet of Things," "Hardware," "Software," and "Mobile," are eliminated.

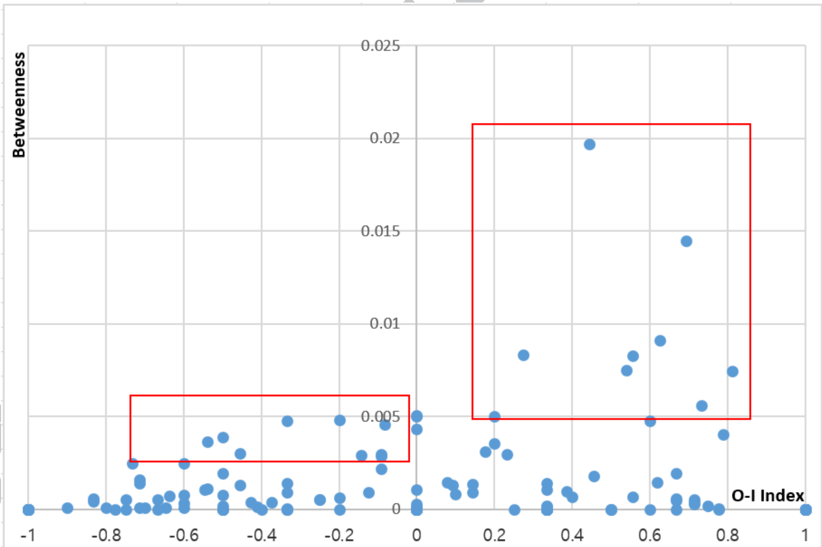
analysis of investors, predicting a need for core technology because the IoT industry has been greatly expanding. On the other hand, IoT startups may not have been able to diversify their ideas in the IoT field yet, resulting in basic technologies in manufacturing and software. However, absorbing groups that are mostly younger and have been funded later show diverse keywords and various new technologies, which could signal more diversification as ideas and know-hows have grown and evolved from the initial stages.

Entrepreneurs of spillover startups have established their own startups regardless of the region or state, whereas absorbing startups are concentrated in California, especially the bay area. Thus, it could be assumed that at the initial stages of the IoT boom, many firms based on basic core technologies throughout the nation have been transformed or have, perhaps, evolved to IoT startups. However, at the later stages, IoT-focused startups have gathered specifically in the bay area for more efficient knowledge sharing. The actual distance between startups and also between investors also has a great influence on the efficiency of knowledge sharing. By clustering together, a faster and more diverse way for new technology convergence can be experienced. We, therefore, assume that the “absorbing groups” have clustered together.

Spillover startups develop their idiosyncratic ideas; however, absorbing startups share their technological ideas and knowledge with each other to exploit the resources of venture capitalists, specifically in the same region.



<Fig. 5> O-I index and betweenness centrality of the serial network model



<Fig. 6> O-I index and betweenness centrality of the clique network model

Spillover	Region	Size	Serial	Clique	Categories
Filament	Reno, NV	11-50	O	O	Bitcoin, Hardware, Software, Internet of Things, Industrial
Keen Home	New York, NY	11-50	O	O	Home Automation, Wireless, Hardware, Software, Internet of Things
uBeam	Santa Monica, CA	11-50	O	O	Consumer Electronics, Wireless, Hardware, Internet of Things
Placemeter	New City, NY	11-50	O	O	Local, Analytics, Finance, Big Data, Mobile, Internet of Things
Helium	San Francisco, CA	11-50	O		Internet, Wireless, Telecommunications
Ayla Networks	Sunnyvale, CA	51-100	O	O	Software, Manufacturing, Internet of Things
Ambiq Micro	Austin, TX	11-50	O	O	Wearables, Semiconductor, Internet of Things
Dash	New York, NY	1-10	O	O	Finance, Hardware, Software, Big Data, FinTech, Mobile, Internet of Things
Revolv	Boulder, CO	11-50		O	Home Automation, Software, Internet of Things
Buddy	Seattle, WA	1-10		O	Internet, Cloud Data Services, Enterprise Software, Mobile, Internet of Things

<Table 1> Description of the “spillover” group

Absorbing	Region	Size	Serial	Clique	Categories
Notion	Denver, CO	11-50	O	O	Home Automation, Wireless, Internet of Things
LaunchKey	Las Vegas, NV	11-50	O		Identity Management, Cyber Security, Security, Mobile, Internet of Things
Eight	New York, NY	1-10	O	O	Health Care, Consumer Electronics, Innovation Management
Cuseum	Boston, MA	1-10	O		Social Media, Art, Mobile, Internet of Things
21 Inc	San Francisco, CA	1-10	O		Bitcoin, Hardware, Big Data, Internet of Things
Butterfleye Inc	San Francisco, CA	1-10	O		Home Automation, Consumer Electronics, Video Streaming, Hardware, Software, Internet of Things
Next Thing Co	Oakland, CA	11-50		O	Consumer Electronics, Internet of Things
TrackR	Santa Barbara, CA	11-50		O	Android, Developer Tools, iOS, Insurance, Mobile, Internet of Things
Moxxly	San Francisco, CA	1-10		O	Health Care, Product Design, Hardware, Software, Internet of Things
Sproutling	San Francisco, CA	11-50		O	Wearables, Parenting, Hardware, Software, Internet of Things
Whistle	San Francisco, CA	51-100		O	Apps, Software, Electronics, Mobile, Internet of Things
Petcube	San Francisco, CA	11-50		O	Robotics, Consumer Electronics, Hardware, Software, Mobile, Internet of Things
Breathometer	Burlingame, CA	11-50		O	Health Care, Quantified Self, Consumer Electronics, Hardware, Software, Mobile, Internet of Things

<Table 2> Description of the "absorbing" group

5. Discussion

Our study provides valid confirmation that investors are the key source of knowledge spillover within the startup ecosystem. The results mentioned above reveal that investors work as intervening nodes for startups to be connected with each other within the network. The results show the importance of the role of investors in knowledge flow. Further, our results challenge the studies that define the traditional role of venture capitalists as selection, monitoring, and financing (Dutta and Folta, 2016). While we explain that the network topology with the investors included is adequate for knowledge transfer through co-occurrence analysis, explaining technological convergence through keywords may not be entirely accurate to explain the flow of knowledge from one startup to another. More qualitative evidence, or perhaps, measures such as the usage of patents or copyrights could be more accurate for such research. However, due to the limitations and characteristics of startups at early stages, startups may not possess such assets. Despite such limitations, our research argues that technology convergence within the startup society is highly influenced by investors by adding a new key feature and role of investors. Hence, the role of investors could exceed the traditional findings and extend to transmitting knowledge or other resources to different firms.

We believe that investors tend to pass on such knowledge because of the returns they receive due to the collaboration of such startups. Eventually, by supporting the success of startups, investors are able to gain greater financial success, participate as members of the board, and elevate their position within the startup society. Investors with such benefits are required to support the success of startups not only in terms of financial performance but also in other aspects. Because investors have multiple investing links, the stock of knowledge increases due to their experience from prior investments and thus, may be used to accelerate technology development by passing on such knowledge. Startups may benefit greatly from the knowledge created by other startups and perhaps other research institutes or incumbent firms connected by the social capital of investors. Interestingly, our analysis confirms that investors hold an important position within the network as bridge nodes or connecting nodes. Investors may, therefore, be the key channels for technological knowledge flows due to the benefit of both startups and investors and also due to the unique position that investors hold in the network. Firms may be able to innovate more as they have internal and external technology advice and support. Another inference that can be made from our study is regarding the initial strategy of early stage startups. When entrepreneurs in high-tech related industries choose the source of investments, rather than fully relying on the terms of the financial offering, the number of links or, perhaps, the number of prior investments should be considered as well. Industries such as the IoT industry may need strategies such as application convergence or, perhaps, lateral convergence. The disruption that occurs while combining existing technologies as a solution for new value creation can bring about disruptive innovations through the application of several combinations of technology. Further, by allowing the breakthrough feature to existing technologies, the attractiveness of the new product or service can grow greatly, creating a new opportunity especially for startups. Prior research may have focused on startups affecting innovation at the industry level; however, they lacked information on how innovation can occur. This study could be extended to see how technology for innovation is created and enhanced.

Clearly, there are other limitations to this study. The measure of technology convergence, which was represented by the alignment of keywords, has its pros and cons. Because a startup company classifies the technology set it uses, keywords could be the most practical explanation of the startup. Further, because knowledge is a vague concept of measurement, especially when firms such as startups lack intangible properties as patents and copyrights, using keywords as a measure to classify technology could be justified. However, because the keywords are arbitrary, there are concerns regarding the accuracy of such measures. Further, although our results confirm that technology is converging in a serial time order, it would be remiss to not acknowledge that the results are limited to the IoT industry. The reason for the selection of this industry is mentioned above; however, the characteristics of startups and investors could differ with each industry. Therefore, the sample could be extended to other industries. Supplemented information on links, such as the investment amount or rounds of investments, might also be able to reveal different attributes of the network. With further effort, this research can be extended to different industries and perhaps offer more accurate measures.

6. Conclusion

This research shows the flow of knowledge through venture capital investments within the IoT venture industry. Through this study, we can obtain an overview of related networks and the flow of knowledge resulting in technological convergence. The main findings show that (1) the startup ecosystem is intensively connected forming a network through venture capitalists, (2) the network is constructed with a major component, that is, the relationship between startups having the same venture capitalists, (3) knowledge is transferred among startups by the investors, and new technology is created due to such knowledge transfer as startups converge the existing technologies in the IoT startup ecosystem, and (4) startups are divided to technology spillover firms and technology observing firms due to their characteristic and network topology within the ecosystem. Our results show that IoT startups have created new technology due to the role of investors transferring knowledge within the entrepreneurial environment. This study not only defines the channel of knowledge transfer in the IoT startup ecosystem, but also finds the characteristics of the technology and the startups that share such technology within the startup ecosystem. Our studies differs from the previous studies by showing empirical results of knowledge transferring within the IoT startup ecosystem and specifically finding that major investors tend to offer more diverse knowledge to startups in the case of IoT startups. This perspective will be able to provide a better understanding about how knowledge and information are passed on and who takes benefit of the knowledge within the IoT ecosystem. Most research on the IoT field has been dominated on the technological aspect, focusing on the development and integration of IoT technologies. We hope the research will inspire other researchers to join us in further studies to find how knowledge is transferred and converged in the startup ecosystem and also focus on the social and political aspects of the IoT industry.

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Highlights

- The IoT startup ecosystem is formed as a large network between investors and startups with one major component and several isolated satellites.
- Startups within the main component are able to share knowledge among the IoT startup ecosystem, due to the role of investors as knowledge conduits.
- Startups invested by major investors are able to converge more technology as major venture capitals offer various knowledge transferred from the investors.
- Startups can be divided into groups that give technology or receive technology within the ecosystem.
- Technology giving startups are focused on core technology while absorbing startups focus on consumer friendly technology with new combined technologies.