Explaining industry emergence through focal key activities in interorganizational innovation networks: A longitudinal study on the autonomous vehicle industry

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Résumé :

This paper aims to explain the industry emergence following a disruptive innovation through key activities (KAs) in interorganizational networks, i.e. the structural components of innovation that are actors and their interorganizational network. Based on the literature on interorganizational relationships (IORs) and disruptive innovation, we create a link with Adner's ecosystem-as-structure construct to argue that the innovation networks could be used as an assessment tool to highlight key activities rather than focal companies to explain industry emergence. To explore our argument, we developed a longitudinal innovation network analysis of the autonomous vehicles industry from 2011 to 2019 based on a unique database encompassing 545 IORs. Our key findings revealed that IORs could be used as metrics for illustrating the emerging years of an industry, while also supporting Adner's construct on ecosystem-as-structure as IORs for autonomous vehicles emerge around five key activities (i.e. connectivity, artificial intelligence, design and commercialization, sensing and Mobility-as-a-Service). In doing so, we reveal the interest to adopt a yearly macro analysis for explaining industry emergence.

Mots-clés : Industry emergence, disruptive innovation, interorganizational innovation networks

INTRODUCTION

The concept of disruptive innovation has seen a growing interest from companies and practitioners (Christensen et al., 2018) because companies either “innovate” or “die” (Kavadias & Chao, 2007: 387). Introduced by Christensen (1997), the theory of disruptive innovation is considered as a powerful instrument in the view of considering innovation-based growth, however, little attention has been allocated to measuring industry emergence triggered by disruptive innovation (Christensen et al., 2018). Defined by Christensen et al. (2015: 1044) as “any new technology or startup that aims to shake up an industry and alter its competitive patterns”, disruptive innovation has the capabilities to disrupt an existing industry, thus industry players, and dislocate the value within the industry or trigger the emergence of a new one. By inference, disruptive innovation is not an easy topic to manage for companies and studies have shown that established companies (incumbents) nearly always win in implementing sustaining innovations that do not imply consumer habits alteration (Christensen, 2006), while new entrants will master in bringing disruptive innovation to the market.

Amongst years, scholars have found a consensus on considering that innovation is enabled through knowledge, and knowledge is best acquired through IORs (Contractor & Lorange, 2002; Malmberg & Maskell, 2002; Kackie et al. 2014). Literature split into two streams, one stream of the literature focused on the challengers’ strategies (Christensen, 1997; Ansari, Garud, & Kumaraswamy, 2016; O’reilly & Tushman, 2016) while the other on the incumbents’ dilemma (Christensen, 1997; Chandy & Tellis, 2000; Jiang et al. 2011; Ansari & Krop, 2012) when facing disruptive innovation. In both cases, IORs are used by companies to support their growth (Oliver, 1990) and participation in disruption (Najafian & Colabi, 2014). However, after our review of IORs and industry emergence, we highlight a gap that is of high importance: how do we assess industry emergence? Therefore, our study aims at shedding light on how companies can measure and identify the dynamics of a new industry that is emerging due to disruptive innovation and places the attention to a macro-analysis level through the observation of interorganizational innovation networks at the industry level. We follow the following research question, which aims at understanding how interorganizational relationships can serve as metrics for industry emergence in a disruptive context.

In order to answer our research question, we focused on the emergence of the autonomous vehicle (AV) industry from 2011 to 2019. We adopted a longitudinal innovation network analysis on the AV industry and collected 545 IORs contracted by companies in the view of developing those types of vehicles. Following the socio-centered data collection method, we framed our data collection with the following question: “In the context of autonomous vehicle industry, what companies contracted an interorganizational relationship, for which specific activity, and when (the year)?” and obtained information on each IORs (the companies involved, the application, and the year).

Our key findings revealed that IORs could be used as metrics for detecting the emerging years of an industry, while also supporting Adner’s construct on ecosystem-as-structure as IORs for autonomous vehicles emerge around five key activities (i.e. connectivity, artificial intelligence, design and commercialization, sensing and Mobility-as-a-Service). Our results revealed that behind the growing number of IORs contracted hid the AV industry. The empirical data enabled us to identify three phases of the emergence of the AV industry.

In doing so, we contributed to literature in several ways. First, our results highlight that IORs besides being growth strategies are also a way to identify industry emergence when observed at a macro level and measure industry structuration. Their multiplication over the years provides interesting insights into industry emergence. Second, we contribute to Adner’s construct of ecosystem-as-structure (Adner, 2017) as the AV industry emerges around key activities rather than key companies. We argue that as disruptive innovations are complex and unknown to companies, tendency falls back in adopting IORs to develop one sub-innovation serving the final one. We add on Adner’s construct by allocating a longitudinal analysis of innovation network emergence. Indeed, we argue that KAs do not emerge by solo incentives taken by companies, but through IORs and the identification of KAs is crucial in the pattern identification process.

LITERATURE BACKGROUND

FROM DISRUPTIVE INNOVATION TO INDUSTRY EMERGENCE

In a context of breakthroughs that demand a wider range of intellectual and scientific properties, companies are facing challenges to gather the knowledge and have to give themselves the means to acquire needed skills in the view of bringing innovation to their clients. Indeed, there is a common belief that innovation relies on knowledge and resources. This has placed knowledge acquisition and reduction of risks at higher importance for companies wanting to increase their innovativeness. Innovation is defined as "the development and implementation of new ideas by people who over time engage in transactions with others within an institutional context" (Van de Ven, 1986: 591). Angelmar (1990) described innovation-related competitive advantages as the assets that give the strongest competitive advantages to companies, while Adhikari (2011) considers innovation as a prerequisite for companies which want to be a leader in their industry. According to Adhikari (2011), innovation can bring paradigmatic change in any industry. However, we argue that limited research is based on assessing the paradigmatic changes that ultimately cause the emergence of a new industry. This is more obvious in the case of a particular type of innovation, the disruptive one, which provokes major shifts in the industry.

By laying the foundation of the disruptive innovation theory, Christensen defined disruptive innovation as "any new technology or startup that aims to shake up an industry and alter its competitive patterns" (Christensen et al., 2015: 2). The primary focus on research on disruptive innovation, despite being misused (Christensen et al., 2018), relies on the complexity for companies to manage it at the organizational level (Christensen, 1997). In most cases, incumbents tend to consider disruptive innovation as foes and dilemmas (Christensen, 1997) which they need to fend off of rather than appreciating them as the main component of economic growth (Aghion & Howitt, 1992), especially as innovation and economic performance have been generally accepted to be closely linked (Koenig et al., 2019). We argue that incumbents lack insight regarding the effects of disruptive innovations on the emergence of the new and attractive industry. What made the study of disruptive innovation even more interesting and more so crucial for industry disruption is the ability of new entrants, also called disruptors (Ansari et al., 2016), to disrupt the existing industry by entering at the bottom of the industry with the view of moving upmarket. Usually, disruptive innovation over time constrains the established industry to waive existing paradigms and move forward.

In the view of identifying the anomalies of the disruptive innovation theory, and reinvigorating research around it, the focus was given to the locus of disruption (Van de Ven, 1986) with some more detailed categorizations (Markides, 2006). We argue that identifying the locus of disruptive innovation could lead to identifying the emergence point of a new industry. The traditional disruptive theory unfolds the tendency of new entrants to enter the existing industry from the bottom and move upmarket with "low-end disruptions" (Christensen & Raynor, 2003). "New-market" disruptions by opposition to the latter embody innovation that arises in a completely new industry with a new value network. New entrants make efforts to conquer a completely new set of customers, both unfamiliar with incumbents' products or services, whilst also being unknown by them. We argue that search and assessment of industry emergence patterns should be observed at the "new industry" disruptions level, as studies on industry emergence at a macro level are limited.

FROM INDUSTRY EMERGENCE TO INTERORGANIZATIONAL INNOVATION NETWORK

Defined as the relationships that occur between suppliers, clients, competitors, diverse partners, interorganizational relations (IORs) are engaged in the view of gaining access to tangible and intangible resources that the partnering companies do not have access to in the first hand (Mandard, 2015). In that view, Oliver (1990) developed six critical contingencies of IOR formation. It, therefore, follows that if two or more companies create a joint venture (Oliver, 1990), they will increase their market power while also doing so on market entry barriers, benefit from synergies in technology and information sharing while sharing risks in entering new markets for instance. As a fact, the motives behind IORs have been largely explored by researchers and innovation seems to represent one of the major reasons (Hulsink, 2008).

We assume that IORs in the view of gaining access to new knowledge, hide the underlying benefit to make companies potential innovators. In fact, external resources acquired through IORs enable companies to overcome complexity brought by technologies (Eisenhardt & Schoonhoven, 1996), enter new markets by gaining market knowledge (Hamel,

1991) while overcoming barriers to entry (Narula & Dunning, 1998), and coping with the newness of a technology or a service (Berry, 1983). Despite being strong competitive advantages (Lin et al. 2010), resources can become scarce within companies (Oliver, 1990), provoking the need to engage in IORs.

When observed at the industry level, discussions regarding IORs (Najafian & Colabi, 2014), coupled with the concept of innovation, led to the concept of an interorganizational innovation network. Following the Schumpeterian tradition, the concept of interorganizational innovation network describes the structural components of innovation: actors and their interorganizational network and has attracted much researchers' attention (Ahrweiler & Keane, 2013). As such, the consequences of such a concept on innovation and company performances have been studied. Scholars have, for example, outlined a positive correlation between IOR network and innovation, although empirical shreds of evidence seem to refute theoretical findings, some consider networks as critical factor success for innovation (Kallio et al., 2010).

For the rest of this paper, we consider interorganizational innovation networks as the set of all IORs amongst companies for the purpose of innovation. We consider IORs are the inherent reasons that drive innovation networks' drivers and performances (Assimakopoulos, 2007). Our proposition is anchored in a setting of industry emergence caused by disruptive innovation, and innovations evoked in the hereby study aims at counterbalancing the effects of the disruptive innovation, or keeping up with it. Although IORs have known growing interest in understanding organizational behaviors (Börjeson, 2015), few studies focus on these IORs' role in the industry emergence (Paprzycki, 2013). To fill this gap, we aim at extending our understanding of IORs in analyzing their role in the emergence of an industry caused by disruptive innovation.

INDUSTRY EMERGENCE THROUGH INTERORGANIZATIONAL INNOVATION NETWORKS AROUND KEY ACTIVITIES

Despite increasing attention since the seminal work of Schumpeter (1942) who introduced the concept of destructive creation, the emergence of the industry has not been studied through the lens of interorganizational innovation networks. Indeed, industry emergence has been studied through various perspectives: being spatial emergence (Ter Wal & Boschma, 2009), or agglomeration around activity regions (Malmberg & Maskell, 2002) such as software and hardware in China and India for example (Gregory et al., 2009). Great attention was also given to the examination of cyclical technological changes (Anderson & Tushman, 1990) while other researchers focused on finding explanatory determinants for industry emergence (Travis et al., 1998) such as the structural and regulatory conditions that can influence industry emergence (Ruan et al., 2014) or the influential effects of technological and categories co-evolution on industry emergence (Grodal et al., 2014).

Regarding the role of interorganizational innovation networks in the industry emergence, it has been less studied. However, we can make a parallel with the concept of ecosystems-as-structure developed theoretically by Adner (2017). Relying on innovation, this concept is very close to the one of interorganizational innovation networks. More precisely, Adner (2017: 40) defines ecosystems-as-structure as the "configurations of activity defined by a value proposition". Activities are themselves defined as the "discrete actions to be undertaken in order for the value proposition to be created" (Adner, 2017: 44). In the hereby study, we will call them Key Activities (KAs) as they can be central for a product or service in a given industry. Actors that are positioned in specific steps of activity flows and carry out exchanges with other companies to which they are linked undertake these actions.

We will use Adner's construct to model relationships amongst companies in regards to KAs. Indeed, the perspective on ecosystem-as-structuration, which remains understudied compared to ecosystems-as-affiliation, could be used to explore our understanding of the emergence of an industry caused by the disruption of the traditional one and study its evolution patterns around key activities. These KAs emerge through the proliferation of interorganizational innovation networks around each of them. This theoretical framework could bring us empirical results to highlight the complex links between disruptive innovation, interorganizational innovation networks and industry emergence.

In addition, important discussions around industry emergence are focused around the company level, where the challenges of the very incumbents and the new entrants have been studied through the theory of disruption (Christensen et al., 2017) and the disruptor's dilemma (Ansari, 2016). The challenges brought by disruptive innovations, as well as the way they have to be addressed by companies, either the incumbents or the disruptors, have been at the center of interest for researchers (Ansari & Krop, 2012). Missing is the consideration of industry creation with the emergence of innovation networks that emerge through the constellation of interorganizational innovation networks around key activities (Adner, 2017). Through the participation in those networks, companies will gain access to information, knowledge, and resources, and develop innovative technologies and this will have an impact on industry emergence patterns.

This study aims at capturing the effects of companies' interorganizational network on industry emergence triggered by disruptive innovation. Indeed, we argue interorganizational innovation networks constructing around key activities (KA) enable that industry emergence caused by disruptive innovation. To address this gap, we propose to conjugate the industry emergence with innovation networks (the puzzle), which are IORs (pieces of the puzzle) between industry in the view of innovation, to assess the patterns of evolution of an emerging industry triggered by disruptive innovation. By inference, we need to analyze the IORs composing the network to seize evolution patterns of industry emergence.

To summarize, little interest has been allocated to consider interorganizational innovation networks as dynamic assessment and metric tools in industry emergence settings. Indeed overestimated are the effects of interorganizational innovation networks on innovation, while underestimated are dynamics brought by the latter at industry emergence level (a macro-level). The hereby study aims at identifying the dynamic of the emergence of industry following disruptive innovation. More precisely, this dynamic is explored the ways innovation networks, through key activities, shape the emergence of an industry. In the following section, we assess innovation networks and apply Adner's (2017) construct of an ecosystem-as-structure in the view of studying the emergence of a particular industry: the autonomous vehicle industry.

THE EMERGENCE OF THE AUTONOMOUS VEHICLE INDUSTRY: A LONGITUDINAL INNOVATION NETWORK ANALYSIS

RESEARCH SETTING

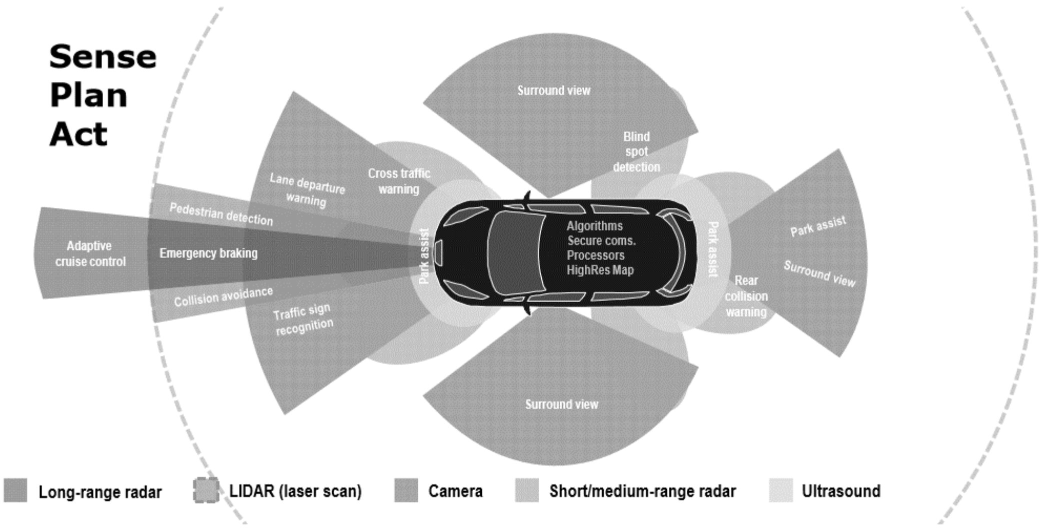
In recent years, the traditional automotive industry is transforming with the appearance of electric and autonomous vehicles. Despite being cleaner (electric), vehicles are more and more equipped with automation functionalities (autonomous) that make them safer (Heineke et al., 2017). Autonomous vehicles (AVs hereafter) are disruptive by definition as they change the way of transporting people from point A to point B. In that sense, the automotive industry faces disruption at several levels. First, technology-wise, AVs are completely different from traditional vehicles as their components and modules are based on autonomous driving systems that are highly artificial-intelligence-dependent. Second, which is a consequence of the first disruption, invalidity of paradigms in the automotive industry landscape invaded with new entrants that may or may not be from the automotive industry at the first place.

Technologically speaking, AVs follow a "sense-plan-act" design of which every robot system is composed. Transforming the vehicle from a transportation mean to a robot destined to drive itself is causing disruption in the traditional automotive industry, and in mindsets. Technology-wise AVs rely on Automated Driver-Assistance Systems (ADAS) that assist the driver in a variety of tasks as described hereafter.

> "These systems can take over the control from the human on assessing any threat, perform easy tasks (like cruise control) or difficult maneuvers (like overtaking and parking). The greatest advantage of using the assistance systems is that they enable communication between different vehicles, vehicle infrastructure systems and transportation management centers." (Kala, 2016: 59).

Therefore, AVs industry is a schism between the automotive industry, telecommunications and information technologies (Heineke et al., 2017). As such, one company does not have all the knowledge necessary to bring autonomous vehicles on the market alone. Indeed, AVs by definition represent a highly complicated technology at which incumbents may not be expert. In order to make vehicles drive autonomously (i.e. drive without driver), companies have to equip vehicles with a cohort of sensors and cameras (i.e. Long-range radar, LIDAR, Camera, short/medium range, ultrasound) in order to feed the ADAS (Figure 1), such as Lane Keep Assist, Valet Parking and Emergency Braking Systems.

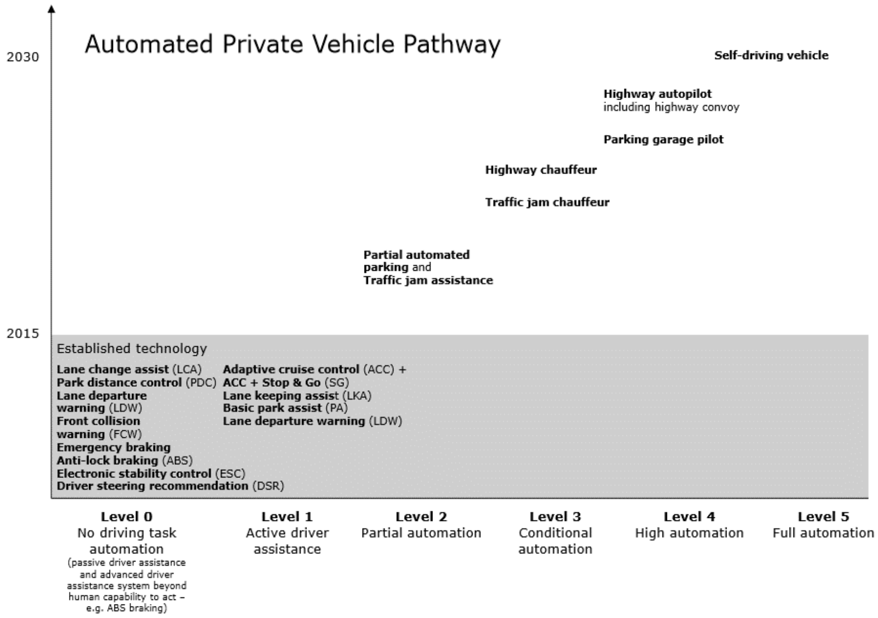
Figure 1. Sensors, cameras and ADAS in autonomous vehicles (Source: OECD, 2018)



Despite being disruptive, AV development will be evolutionary and, as such, were developed five levels of automation by the Society of Automotive Engineers (SAE International, 2014)[1]: no driving task automation, active driver assistance, partial automation, conditional automation, high automation and full automation. The International Organization of Motor Vehicle Manufacturer (OICA) also developed a five-level classification in order to "address legal and technical aspects" of autonomous driving while also proving a glossary of terms very similar and based on the SAE J3016 guidelines. The equipment rate of AVs therefore depends on their level of automation. These different levels split the responsibilities between the driver and the different ADAS functionalities (Figure 2).

Figure 2. ADAS systems according to their level of autonomy (Source: International Transport Forum, 2015)

[1] The Society of Automotive Engineers (SAE) is a non-profit organization operating in educational and scientific fields. The 90,000 engineers focus their research around mobility technology in order to better move humans with automobiles, trucks and busses for road transport.



At level zero, there is no driving tasks automation, automated driver-assistance systems only come to support the driver in his driving tasks, and carry out monitoring functionalities. For instance, the ADAS functionality of "Lane change assist" helps the driver to monitor its environment before initiating a lane change, while "Lane departure warning", in cases where the driver dislodges from the lane, comes to warn the driver to reenter in the lane properly.

In level one, active driver assistance functionalities are incorporated such as "Lane keep assist", which will physically force the vehicle to stay in the lane by following road signs on the ground. At level two, SAE considers automation is conditional. Indeed, the vehicle can execute autonomous driving tasks in given contexts such as parking and traffic jams, OICA speaks about "dynamic driving tasks" when the vehicle can perform lateral and longitudinal driving tasks after having scan its environment. At level three, AVs reach conditional automation, the highway chauffeur or the traffic jam chauffeur will replace the driver in given situations (i.e. on the highway, during traffic jams).

At level four, the vehicle corresponds to high automation as the vehicle is equipped with autopilot systems that mimic a driver's behavior and do not need the driver's action to drive autonomously. Ultimately AVs will reach level five of full automation and the vehicles will serve as robots to transport people where no drivers' seat is available. From level zero to three, the vehicle requires a licensed driver, whereas it is not needed in levels four and five (SAE International, 2014).

AVs represent thus a very interesting and comprehensive case study and being a disruptive technology; it brings together companies from different industries and link them through IORs. As the auto industry is migrating towards more autonomous vehicles (AVs) every major automotive original equipment manufacturer (OEM) carry out research and development activities in this disruptive technology (e.g. General Motors' acquisition of Cruise Automation in 2016) but also the help of new entrants. Even more, AVs industry is very contemporary topic that is fast evolving. IHS automotive forecasts that by 2030, twenty-one million AVs will hit the road.

DATA COLLECTION

Social Network Analysis (SNA hereafter) mainly aims at investigating social structures with network, graph theory, and strongly endorsed by Tichy, Tushman, and Fombrun, (1979) to apply in management fields. SNA is adopted (Freeman, 2004) as a key technique in modern research to visualize and conceptualize social structures and relations and applied to many levels, interorganizational level being one of them (Borgatti & Foster, 2003). SNA is applied to many different fields and shadow spots still remain when it comes to fundamental guidelines of data collection (Monaghan et al. 2017).

Amongst years, two perspectives on SNA have been developed: the socio-centered network and the ego-centered network. We will build on the first one (the more central node of the network) usually used for quantification of relationships between people or institutions within a defined group. The focus is put on measuring the structural patterns of those interactions and how this explains the dynamics in pattern of industry emergence year by year. Based on this choice of methodology, we collected data according to it.

Our main source of data was IHS Automotive, the automotive market intelligence platform that provides auto companies with industry scanning reports, articles and forecasts. IHS Automotive is well-known in the automotive circle. Its strength lays in its capability to provide both automotive stakeholders and shareholders (OEMs, and Tiers) with information regarding OEM brand strength, market shares, technology adoption pace, growth and segment trend monitoring. The platform is a comprehensive market intelligence tool used by automotive companies to monitor their industry and shape their strategies according to the trends.

Adapting the data collection in order to observe the ego-net emergence, our starting point was the relation of interest, the companies involved and, the year. In order to come up with a roster of company names, and the key activities for which they decided to collaborate, we guided our data collection by a framing question: "In the context of autonomous vehicle industry, what companies contracted an interorganizational relationship, for which specific activity, and when (the year)?". We start our collection in 2011 as the very first articles published by IHS Automotive on this subject has to be published this year. We ended our data collection, the 31st of December 2019. During this eight-year period, we have identified, through the adjacency matrices (where for a simple graph with vertex set V, the adjacency matrix is a square $|V| \times |V|$), 545 IORs that encompass 439 companies.

We also collected interesting insights in press releases issued by McKinsey, Automotive News and AutoWorld to endorse our quantitative data. To have a deeper understanding of the complex technologies behind AVs, we also participated in three specialized worldwide conferences: AV Conference Silicon Valley 2018, 3rd Annual Singapore AV Conference 2019 and AUTO.AI Berlin 2019.

DATA ANALYSIS

To analyze our data, we followed three complementary steps. First, we carried out a categorization work to classify the specific activities in more macro-categories, also called Key Activities (KA). Second, we worked on the seminal findings to both characterize these KAs and the interorganizational innovation networks around them.

First, we focus on the different specific activities identified (which) to analyze how they can share some common points and belong to a more generic category (KA). Indeed, some activities share the same technology for example, or share the same goal, the same function and can be aggregated to a broader category, i.e. the key activities (KA) necessary for AVs to become marketable.

Below is an example of the 867 articles collected that illustrates the reasoning that we have followed to create our KA categories. In the article entitled ‘General Motors acquires Lidar specialist Strobe’ published on 9th October 2017 in the IHS Market, it is announced that General Motors (who), a giant American automotive manufacturer, acquired the Lidar (which) specialist Strobe (who) in October 2017 (when): “General Motors (GM) has acquired Strobe, a California (United States)-based start-up specializing in Lidar technology.” This article stipulates that the acquisition was made in order to strengthen General Motors’ positioning on AV development through the development of a lidar.

“The automaker did not disclose the financial details of the acquisition [...] Lidar sensors, which use laser light to measure distance to objects, are considered a key enabler for autonomous driving. The sensors, when used along with cameras and radar sensors, help a self-driving vehicle to better understand its surrounding and navigate safely with high degree through data sensing”

We classified Lidar as a key activity (the “which?”). For each article mentioning an IOR, we repeated the process of identification and data collection. In fine, we came up with a roaster of activities (i.e. Lidar, radar, software, simulation, machine learning) and created broader categories to archive into them. In the present case, as a Lidar aims at collecting information, we created a KA named Sensing. In that category were classified all the equipment needed to collect information from the interior and in the interior of AVs such as lidars, cameras, radars and lasers

To further illustrate our reasoning, we will give an additional example, regarding another KA: artificial intelligence. The roaster of specific activities encompassing machine learning, pattern recognition, neural network, quantum computing seems to mention artificial intelligence-related specific activities. The number of specific activities played an important role in the choice of KAs.

To assess our categorization, we submitted our grid of analysis to automotive, artificial intelligence and telecommunication experts and journalists who specialize in the AV industry, during the three conferences we participated in. They all confirmed our categorization. All the more, the numerous plenary sessions, workshops and networking breaks were a good way to exchange, discuss and address the categorization while adjusting and enriching it with feedback from the field.

Ultimately, we classified all the specific activities of each IORs (n=545) into five KAs: connectivity, artificial intelligence, sensing, design and commercialization, and Mobility-as-a-Service (Table 1).

Table 1. The Five Key Activities of the Autonomous Vehicles industry

Key Activities	**Definition**
Connectivity	Connectivity enables the vehicles to know where it needs to go through navigation systems based on HD maps, connectivity to the infrastructure (V2I), pedestrian (V2P), other vehicles (V2V) through electronics (Electronic control systems (ECUs), systems-on-chip (SoC), semiconductors) and telecommunication systems (4G/5G, big data, cloud systems).
Artificial intelligence (AI)	AI enables ADAS to navigate safely in traffic and manage complex situations as will humans do through complex algorithms that compose the car's brain. The related activities of AI are for example, machine learning, quantum computing, computer vision, or pattern recognition.
Design and Commercialization	This KA refers to the development of AV fleet (shuttle, taxis, robot-taxis), testing activities as AV need to travel for technology validation purposes (e.g. testing AV level 4 in Shanghai, testing V2X applications.), but also the development of new material geared towards futuristic and refined designs for AV (e.g. new materials, new paints, new seats).
Sensing	Autonomous vehicles are equipped with three types of sensing components: cameras, sensors and LIDAR-based system
Mobility-as-a-Service (MaaS)	This KA is highly critical for AV level 4 and 5 as it will serve as autonomous vehicle service providers. MaaS service refer to

	companies collaborating for Autonomous Mobility on demand (AMod), taxi hailing services, and ride hailing services.

Each KA is complex on its own. The complexity of AV to run smoothly finds its inherent reasons in the wideness of the complex technologies needed. We assume that in order for AVs to be marketable, all five KAs need to be mature and robust in the technology they deliver. Whether it is high definition maps and geo-localization activities in the connectivity KA or machine learning and algorithms developed in the artificial intelligence KA, they should all be integrated into an AV and we argue that they go hand in hand as one serves the other and vice versa.

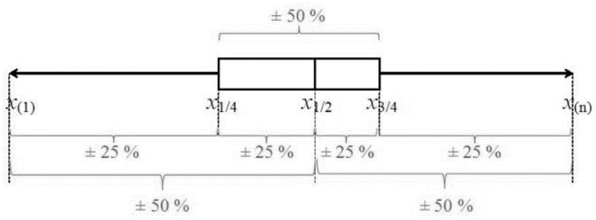
Once we identified the five KAs (Table 1), we decided then to observe the evolution patterns of each one. Thus, we have coded the IORs according to their KAs into square matrices and ran it into NetDraw (Borgatti et al., 2002). We decided to use the graph theory to 1) identify whether our assumptions of IOR innovation networks building around KAs as industry emergence pattern is verified, 2) observe and characterize the evolution patterns of these KAs, thus of the whole AV industry.

For the first and our second main step, we used the R software (R Core Team, 2013) to carry out statistical computing on our database and report the main trends of emergence. We create an R Language algorithm and applied it to the database in order to highlight the main evolution patterns.

For this second aim and thus our third step of the analysis, the companies are symbolized by nodes and IORs by ties between each company. A node in the network represents a company. As we are focusing on conceptualizing the emergence of the industry around KA, “egos” are the key activities (bigger nodes) and “alters” are the companies of the innovation networks (smaller nodes). The size of each node represents its degree centrality, the bigger the size of the node, the higher the degree centrality.

We coded our data in the same manner as for the second step of our analysis and added the attribute of KA for which each IORs is contracted. Indeed, as explained, in the view of developing AVs, companies need to first carry out those five key activities (KAs) that emerged from the database and that are: connectivity, artificial intelligence (AI), design and commercialization, and sensing. Our results highlighted 119 IORs for AI, 173 for connectivity, 97 for design and commercialization, 131 for sensing and 14 for MaaS.

We used descriptive statistics method with a box plot to graphically depict groups of numerical data of IORs through their quartiles. The repartition of data within a box plot occurs as shown below,



, where $x_{(1)}$ is the minimum excluding the atypical points, $x_{(1/4)}$ the first quartile (25th quartile), $x_{(1/2)}$ the median being the middle value of the dataset and $x_{(n)}$ the largest data excluding any atypical points. Atypical points (outliers) are by definition infrequent observations, which is to say points that do not follow the characteristic distribution of the rest of the data.

Furthermore, in order to capture the centrality of each KA, we computed a centrality degree on the whole dataset encompassing IORs from 2011 to 2019. As mentioned before, the size of the nodes is proportional to the number of the incoming vertex. According to Borgatti et al. (2009) at the node level, centrality is the measure that is the most looked at. It refers to "a family of node-level properties relating to the structural importance or prominence of a node in the network" (Borgatti et al., 2009: 894). Therefore, we examined two different centrality degrees in order to corroborate our results.

First, following Rusinowska et al. (2011: 6), a degree centrality "indicates how well a node is connected in terms of direct connections". The degree centrality is given by this formula:

$$C_d(i;g) = \frac{d_i(g)}{n-1} = \frac{|N_i(g)|}{n-1}$$

Where Ni(g) is a set of nodes {1, 2, …,n} with which a node i has a link and di(g) the number of links between nodes i et g. The network is considered complete when d = n – 1.

Second, the Bonacich Eigenvector Centrality is a measure of centrality in which "a unit's centrality is its summed connections to others weighted by their centralities" (Bonacich, 1987: 1173) and considers a wider range of direct and indirect ties that have an influence in networks. In a similar approach as the first one, the eigenvector-related centrality degree examines the idea that the importance of a node is measured by its neighborhood (Rusinowska et al., 2011). This measure is particularly important as it assumes that the importance and prestige of one node is dependent on the centralities of the nodes to which it is linked to (Bonacich & Lloyd, 2001). The formula of the Bonacich Eigenvector Centrality is:

$$x_i = a_{1i}x_1 + a_{2i}x_2 + \cdots + a_{ni}x_n$$

Where x is the centrality score, A et B are adjacency matrix where a_{ij} means that I influences j's centrality (Bonacich & Lloyd, 2001). We applied these two formulas to our data.

FINDINGS

This section is structured around our two main findings. First, we aim at testing our assumptions of IOR innovation networks building around KAs as industry emergence patterns. Then, we propose to observe and characterize the evolution patterns of these KAs.

INTERORGANIZATIONAL RELATIONSHIPS AS METRICS FOR INDUSTRY EMERGENCE

Based on our unique database containing 545 (n) innovation IORs, we collected data that covers 2011 (Min) to 2019 (Max) and the key activities for each IORs. In order to verify our assumptions on the emergence of IOR innovation networks around KA, we first intended to observe the general trend regarding the number of IORs over time (Figure 3).

Figure 3. Number of yearly IORs engaged from 2011 to 2019

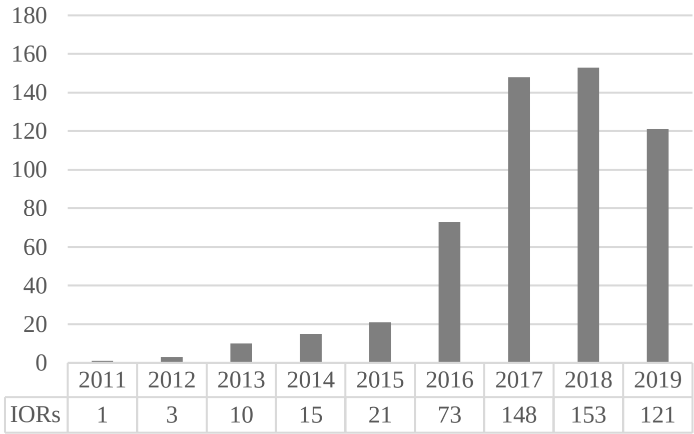


Figure 3 shows that between 2011 and 2019, the number of IORs has increased at a semi-regular pace. Indeed, we see that the AV industry starts to emerge in 2011, however, the drastic multiplication of the number of IORs happens in the following years. The number of IORs steadily increased from 2011 to 2015, we go from 1 to 21 IORs observed in five years, and there are no major patterns to notice. However, in 2016, the increase started to become more noticeable at the point when in 2018 the number of IORs peaked at 153. We assume that 2017 and 2018 marked the emergence of the AV industry by being the busiest years IORs wise. Figure 3 thus enabled us to highlight the multiplying characteristics of IORs amongst years.

Our first result enabled us to corroborate that IORs can be utilized as metrics to assess industry emergence. According to our data, the AV industry started to emerge in 2011. A deeper analysis of the contextual knowledge of the AV industry allows confirming this result.

Indeed, for years' road injuries have been the grey area shadowing the benefits of developing vehicles. As human error is identified as the major explanation of the latter, the tendency falls back into trying to reduce human error with Automated Driver Assistance Systems (ADAS). Thus collected data started to show results from 2011 as the rising interest around the ADAS field strengthened in 2009 with the Toyota-fiasco when 2.2 million cars recalled by Toyota in the US over safety-related issues made the sparks brighter and constrained carmakers and tiers to focus more on these particular topics (IHS Automotive, 2011). As a consequence, regulatory authorities were awakened. For example, the National Highway Traffic Safety Administration (NHTSA) in the United States considered at that time to make fitment of brake overriding system mandatory equipment for future vehicles.

However, Trump's administration recently scrapped the mandate proposed in 2009, even though such features are already installed in new vehicles (Reuters, 2012)[2].

Our second result concerns the slow emergence of IORs within this industry until 2015 and then strong growth until 2016 due notably to the role played by the technical framework developed by the Society of Automotive Engineers (SAE). From 2011 to 2015, IORs were facing quite a steady adoption pace. In fact, companies were quite preservative in terms of their strategic actions. However, in 2016, two years after the introduction of the SAE technological framework for autonomous driving, companies raised strong interest in AVs, with 73 IORs in 2016 against 21 the year prior. Indeed, the taxonomy and definition for terms related to driving automation systems for on-road motor vehicles were issued in January 2014 by this society (SAE International). This technical framework identifies the five levels of automation as described in the research setting: no driving task automation, active driver assistance, partial automation, conditional automation, high automation and full automation. These different levels that make a distinction between the responsibilities of the driver and those of the different ADAS functionalities, had a great impact on the recognition of AVs at a general scale as it rose awareness about new driving technologies and gave a technological framework to which companies could refer. It was even more important as OEMs, tiers and technology companies were the players at the source of these guidelines. In addition, the US Department of Transportation and the United Nations have adopted this framework, and OEMs and automotive suppliers position their product amongst the SAE levels of autonomy that they enable to reach. As from now, industry players have a technical framework to frame their product development. In consequence, the number of IORs thus increased six-fold within the two following years of that implementation.

Our third result highlights a slow decrease trend since 2018. In 2018, the number of IORs was still quite predominant (153) but started to face a decreasing trend and reached 121 IORs in 2019. This slowdown observed in 2019 is explained by many major facts. First, the traditional automotive industry is facing a tumultuous year with production levels that start to hit bottoms. In fact, IHS Automotive registered a 6.3% year-to-year decrease between 2018 and 2019, i.e. 94,204,155 in 2018 against 88,775,550 forecasted for 2019 (IHS Automotive,

[2] https://www.reuters.com/article/us-toyota-recall-prius/toyota-to-recall-2-8-million-vehicles-for-steering-glitch-idUSBRE8AD09A20121114

December 2019). As their traditional industry is quaking and many industry players forced to shut down plants, part of them wants to play it safe and not be absorbed by the high level of investment required for AVs, which represents the second major fact that explains the slowdown observed in IOR adoption. Although there are no general estimations on how important investments in AVs are, PwC (2016) published a report called 'Connected Car study' in which it estimated that the top five of OEM spent $46 billion in research and development in 2015 (Karsten, 2017).

To sum up, this first series of result enabled us to identify the emergence of the AV industry through the multiplication of IORs from 2011 to 2019, even if we observed a specific repartition of IORs over time, with a slow emergence, then a peak and since 2017, a certain slowdown. The following section will be the opportunity to conjugate the proliferation of IORs with the emergence of innovation networks around KA over time.

At that point, our assumption is partially assessed. Indeed, the quantification of IORs enabled us to identify the emergence of an industry. We then aimed at characterizing how these IORs emerge as innovation networks around KAs and thus highlighting the multiple interorganizational innovation networks they sustain for this disruptive innovation to be marketable.

INDUSTRY EMERGENCE THROUGH INTERORGANIZATIONAL INNOVATION NETWORKS AROUND KAS

This section aims at examining the emergence of innovation networks around KAs. We carried out box plot analysis in order to show the gradual emergence of IORs innovation networks around KAs. Figure 4 shows the IORs per KAs.

Figure 4. Box-plot of IORs engaged from 2011 to 2019 by key activity

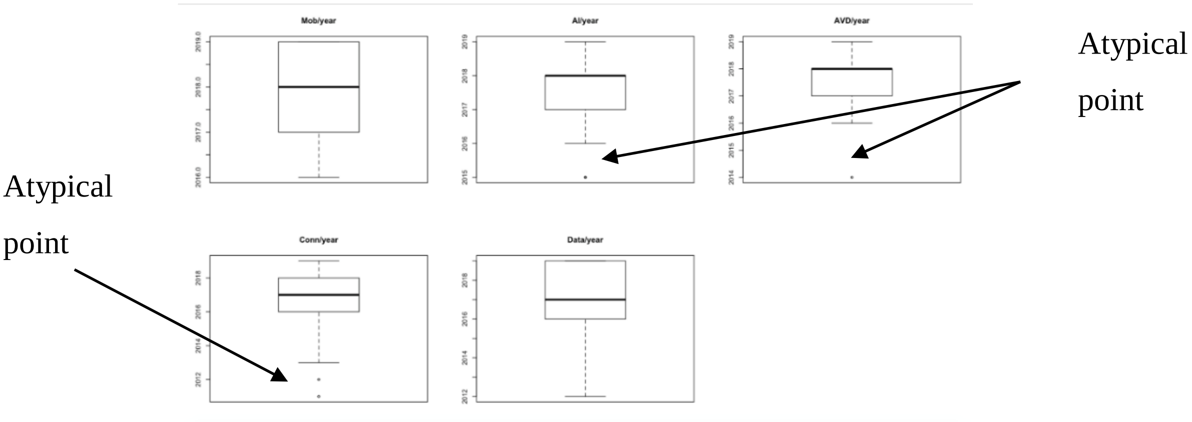


Table 2 summarizes the occurrence of IORs for each KAs over the studied period. We shadowed the atypical points in this table.

Table 2. Start of IORs in each KA, occurrence from 2011 to 2019

	2011	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Connectivity	x	x	x	x	x	x	x	x	x
AI					x	x	x	x	x
Sensing		x	x	x	x	x	x	x	x
Dev and commercialization				x	x	x	x	x	X
MaaS					x	x	x	x	x

Connectivity is the historical KA, meaning that the first IORs seem to be around that key activity in 2011. However, Graph 4 shows that for 2011 and 2012, IORs around connectivity are represented by atypical points. The same observation is made for AI which atypical point is in 2014 and, design and commercialization which properly starts in 2015. Therefore we will consider that the KA connectivity started properly in 2013, AI in 2016 and design and commercialization in 2015.

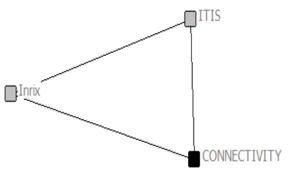
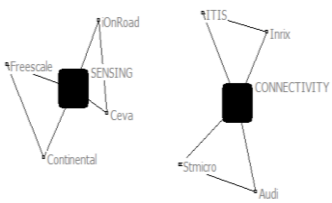
Our results enabled us to identify three distinct phases of innovation network emergence around KAs. First, we have phase 1 were partial and moderated apparition of innovation networks seem to emerge around the KAs connectivity and sensing, the emergence is latent. This phase covers 2011 to 2014 and is the post J3016 Taxonomy phase (SAE International, 2014). Then, phase 2 highlights a two-year cohabitation of all the KAs from 2015 to 2016. We observe increased robustness of innovation network around the KAs connectivity and sensing and apparition of moderated IORs around the KA AI in 2015, followed by the structuration of innovation networks around all the five KAs in 2016. Last but not least, phase 3 is characterized by the reinforcement of the networks around KAs until today. We observe a plethora of IORs inherent of wider and denser innovation networks around the five KAs.

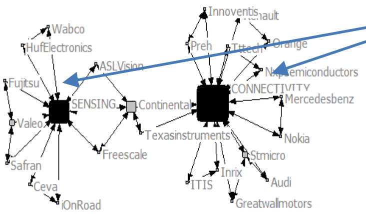
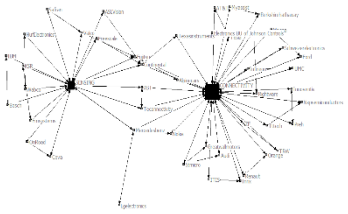
Beyond the numerical distribution by year and by KAs, it could be interesting to conceptualize the networks forming around these KAs thanks to UCINET. The following section is a phased tier-down of innovation network emergence around the KAs.

Phase 1 (2011-2014). The partial and moderated apparition of KA with their innovation networks

Based on our statistical results, we can assess that the first IORs happened around the two KAs Connectivity and then, Sensing. Table 3 illustrates the apparition phase of the first IORs from 2011 to 2014.

Table 3. The first IORs around two key activities: Connectivity and sensing (2011-2014)

Year (Number of companies)	Graph	Observation
2011 (2)		The first IORs around the KA, connectivity. Identification of atypical points for first IORs in Connectivity
From 2011 to 2012 (8)		The apparition of a second IOR around the KA, Sensing

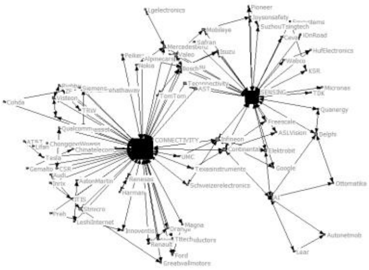
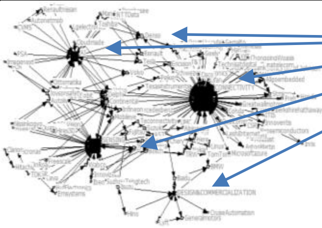
From 2011 to 2013 (24)		Innovation network starting to properly build around those two KAs, connectivity and sensing
From 2011 to 2014 (48)		Intense densification of the IORs around the KA connectivity

From 2011 to 2014, the emergence happens slowly, we identify the first KAs necessary to AVs, which are connectivity and sensing. As mentioned previously, connectivity aims at making the vehicle aware of its internal (driver, entertainment, maintenance) and external (pedestrians, vehicles, traffic conditions based on navigation data) environments. Sensing concerns the equipment of vehicles with different sorts of sensors and cameras. What makes sense is that the willingness to make the car more predictive and automated comes with giving it the means to do so: sensors and cameras (eyes) and connectivity (communication skills).

Phase 2 (2015-2016). The cohabitation of all the KAs

If innovation networks were first building around connectivity and sensing, we observe the apparition of another KA around Artificial Intelligence (AI) in 2015. The industry starts to structure and is composed of more robust innovation networks around connectivity and sensing, and more moderated ones around AI and then the two last KAs, MaaS and design and commercialization that appear in 2016 (Table 4).

Table 4. The emergence IORs around three more key activities: AI, design and commercialization and Maas (2015-2016)

Year (Number of companies)	**Graph**	**Observation**
From 2011 to 2015 (76)		More robust innovation networks around the KAs connectivity and sensing Identification of atypical points for innovation network around the KA, AI
From 2011 to 2016 (117)		The cohabitation of innovation networks around the five identified KAs: connectivity, sensing, AI, MaaS, design and commercialization

In 2015 (2011-2015), the introduction of a new innovation network around the KA of Artificial Intelligence (AI) can be explained by a major acquisition done by Delphi, a traditional automotive part manufacturer. This automotive giant acquired Ottomatika to develop its competences in software for autonomous driving (IHS Automotive, 2015) and has thus attracted interest around such key activity. Ottomatika is an American self-driving vehicle technology developer, providing with software stacks, sensor calibration, and support services.

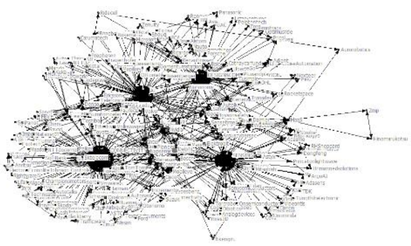
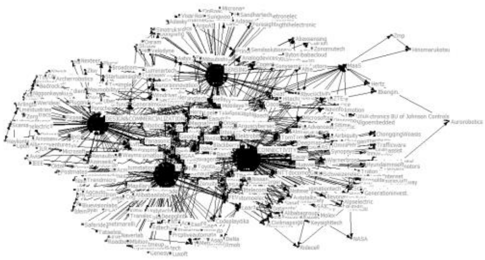
The snapshot of the industry made in 2016 (2011-2016) brings out the appearance of another new KA: the design and commercialization one. This year is also marked by the acquisition of Cruise automation by General Motors in March 2016. Cruise Automation is a California-based startup that develops systems for autonomous vehicles, and a way for General Motors to indirectly communicates about its strategy of becoming a key player in autonomous driving. The same year, Delphi and Mobileye, two leading automotive parts suppliers, announced their partnership to develop an autonomous driving system for 2019 whilst BMW, Delphi and Intel entered a partnership to develop autonomous driving systems for BMW vehicles.

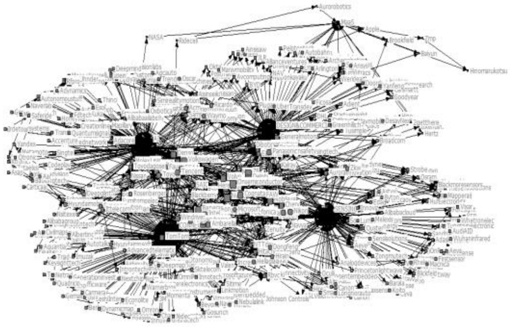
Regarding MaaS, the innovation networks seem to be more pervasive as the network appears in 2016, and the analysis of the following years shows a tendency of a slower emergence compared to the other four KAs.

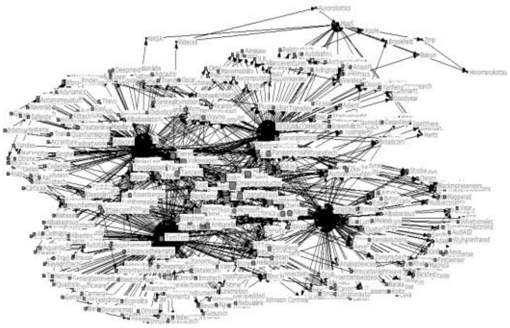
Phase 3 (2017-2019): Plethora of IORs in each KA innovation networks

From 2017 to 2019, the industry gets more structured and the aggregation around each KA is clearly visible and robust.

Table 5. The increase of IORs around the five key activities (2017-2019)

Year (Number of companies)	Graph	Observation
From 2011 to 2017 (241)		Consolidation of innovation networks around each KAs except MaaS which remains more pervasive.
From 2011 to 2018 (359)		The industry is completely submerged with IORs and visibly structured around KAs. AI, Connectivity, Sensing and Design, and Commercialization KAs seem to be very central. The KA MaaS is getting importance.

From 2011 to 2019 (439)		The industry is consolidated. More and more IORs around design and commercialization which is partially explained by the fact that these KAs contain testing activities for products developed before.

From 2011 to 2019 (439)		The industry is consolidated. More and more IORs around design and commercialization which is partially explained by the fact that these KAs contain testing activities for products developed before.

The yearly breakdown of industry emergence clearly shows emergence patterns. The emergence around KAs starts with a phase of latency where IORs are partially developing. The following phase is characterized by the cohabitation of the five KAs, however and despite the consolidation of the following KAs, Connectivity, Sensing and AI, it could not be said that the industry is clearly structured. However, the third phase lets us see the image of a wider, highly populated networks around KAs. Indeed the number of companies involved in these innovation networks increased from 2 (2011) to 439 (2011-2019).

The network analysis enabled us to conceptualize the innovation networks around KAs. The following section aims at understanding what the size of the nodes hides at a statistical level.

Understanding networks through the centrality degree: Evidence of network robustness

In order to capture the centrality of each KA, we computed centrality degree on the whole dataset encompassing IORs from 2011 to 2019 and calculated two different centrality degrees in order to corroborate our results: the degree of centrality according to Rusinowska et al. (2011) and the Bonacich Eigenvector Centrality (Table 6).

Table 6. Bonacich Eigenvector centrality and Degree centrality by KA, 2011-2019

	Connectivity	AI	Sensing	Design and Communication	MaaS
Bonacich Eigenvector Centrality	0.444	0.367	0.303	0.274	0.042
Degree Centrality	0.388	0.335	0.318	0.269	0.053

According to Table 6, each of the KAs is proven to have both a high centrality degree and a high Bonacich eigenvector centrality. This shows that there are innovation networks building around those five KAs. These KAs are central in the global network with relatively high centrality degree measures with connectivity being pervasive, closely followed by AI, and Sensing. Design and Commercialization represents the KA where companies test the developed product and propose them to customers. As conceptualized by the networks presented in the previous section, KAs are central in the global industry. Indeed, we computed the degree with UCINET (Borgatti et al., 2002) and selected the top five nodes with higher centrality degrees. The results obtained through this top-five filter resulted in identifying our five KAs.

DISCUSSION

To conclude our study, we argue that our longitudinal innovation network analysis enabled us to obtain findings corroborating our assumptions on considering IORs as industry emergence metrics. Our empirical data on the AV industry emergence revealed results at two levels and explains the inherent legitimacy of adopting a macro-level analysis. First, the global analysis of the number of IORs from 2011 to 2019 shows great opportunities to seize industry emergence thanks to IORs. Alike a virtuous circle, or motivated by performance promises, companies when aware of other companies' IORs also contract one or more. This, at a macro level, reveals that companies are making an effort to adapt to a change brought by disruption. Second, through computational statistics as well as network analysis, we identified emergence patterns. By doing so, we 1) gave IORs another perspective as we considered them as metrics of industry emergence, 2) observed the emergence of the industry around key activities.

In the same manner, our results empirically corroborated Adner's (2017) construct arguing that ecosystems can structure around key activities rather than focal companies. We supported that view and endorsed it with empirical data, proving that a disrupted industry by definition being highly innovation-driven, needs several key activities for the final technology to be marketable. By working on industry emerging around key activities companies may identify the future of the technology, validate what technology has a future and what does not and can keep track of other companies' strategic trajectories, whether competitors or industry stakeholders.

Thus our results are mostly consistent with the theoretical article of Adner (2017), which predicted the structuration of an ecosystem around activities rather than focal companies (ecosystem-as-structure vs. ecosystem-as-affiliation). Based on our analysis of the emergence of the AVs industry, we predicted an influential effect of innovation networks emerging around key activities, which in turn sustained the emergence and structuration of a new industry. If considered in terms of the gradual evolution of industry emergence, we first found that IORs are a strong tool to identify the change, of course, happening in an industry disrupted by innovation. In term, we identified the beginning of the AV industry emergence. Our second finding resulted from our effort of revealing emergence patterns that we observed over the years. Results showed that in order for a complex and disruptive industry to emerge, several key activities need to be carried out in the first place.

Assessing the emergence patterns of an industry, IORs have been motivated by empirical anchorage of such strategies in a company's way of conducting its activities. We argue that observing companies' IORs strategies at a macro-level can have an impact on industry emergence assessment while also enabling to measure it.

This study addressed these limitations by applying a social network analysis methodology to carry out a longitudinal case study on AV industry emergence.

Our study also provides limitations. Indeed, in order to have more insightful results regarding the nature of the ties, we need to further characterize each node of the network, in order to determine whether or not the type (incumbent vs. new entrant), the industry of provenance of the companies (e.g. automotive, telecommunications) can have an impact on the pace of emergence. This will also enable us to highlight the effect of diversity on industry emergence and attribute variables to the evolution pace of the AV industry.

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