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AI Organizational Learning through Corporate Venture Capital

Using CVC as a tool for Artificial Intelligence learning in France and Japan

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Résumé

Le corporate venture capital (« CVC »), ou capital-risque d'entreprise, est une structure corporative d'investissement ayant pris de l'importance dans les dernières années (Brigl *et al.*, 2018). Les entreprises choisissent d'établir un programme de CVC afin d'atteindre une série d'objectifs stratégiques et financiers (Basu, Wadhwa et Kotha, 2016; Maula, 2007). L'amélioration des connaissances est l'un des objectifs stratégiques qu'elles peuvent poursuivre: les programmes de CVC peuvent constituer pour les firmes des sources de savoir externe (Dushnitsky et Lenox, 2005b). En effet, au travers de son activité de CVC, une entreprise gère des prises de participations minoritaires dans de jeunes compagnies innovantes, telles des startups, et peut potentiellement apprendre de celles-ci. Cependant, la manière dont les activités de CVC contribuent aux apprentissages organisationnels d'une entreprise reste largement inconnue. Cette situation est particulièrement vraie lorsque des programmes de capital-risque investissent dans des startups ayant des savoirs complexes, ambigus. Cette recherche a pour objet de répondre à ces questionnements en étudiant le lien existant entre activités de CVC et apprentissages organisationnels. Elle le fait au travers d'une analyse de la contribution des structures de CVC à l'apprentissage de l'intelligence artificielle (IA), un ensemble de technologies réputées complexes, chez leurs compagnies mères. Cette recherche se base sur l'analyse de dix organisations ayant participé à des activités d'IA en France et au Japon, incluant sept programmes de CVC.

Les résultats montrent que le CVC permet à une entreprise d'acquérir des savoirs généraux et commerciaux sur l'IA. Les activités de CVC ont permis aux entreprises mères à mieux reconnaître la valeur et l'attractivité de solutions d'IA, à assimiler plus rapidement des solutions d'IA et à traduire des opportunités d'IA en solutions commerciales. Cependant, ces programmes ne peuvent se substituer aux efforts de R&D d'une entreprise, ne permettant ni un transfert de savoir technologique ni une rétention de connaissances d'IA. Ils n'influencent pas par ailleurs directement la création de nouveaux savoirs d'IA. L'ambiguïté des technologies d'IA, quant à elle, n'a qu'un faible impact sur les activités de CVC.

Mots-clés: CVC, capital-risque d'entreprise, apprentissages organisationnels, transfert de savoir interorganisationnel, capacité absorptive, sources de savoir externe, IA

Abstract

Corporate venture capital (“CVC”) is a corporate venturing structure that has grown in importance in recent years (Brigl *et al.*, 2018). Organizations establish CVC programs to complete a series of strategic and financial objectives (Basu, Wadhwa et Kotha, 2016; Maula, 2007). Learning is one of such strategic objectives, as CVC programs can be used as external knowledge sources for companies (Dushnitsky et Lenox, 2005b). Through CVC programs, companies manage minority equity investments into young, innovative ventures firms such as start-ups. Using CVC, firms could potentially learn from their innovative partners. Yet, the way and extent to which CVC activities contribute to their companies’ organizational learning remain unclear. It is especially the case when CVC invest in start-ups exploiting intricate and ambiguous pieces of knowledge. This research attempts to answer these questions by studying in detail the relationship existing CVC and organizational learning. It does so by analyzing how CVC activities contributed to their parent companies’ artificial intelligence (“AI”) learning, an intricate and ambiguous set of technologies that has attracted considerable attention in recent years. This paper is based on ten case studies of companies engaged in AI activities in France and Japan, including seven CVC programs.

Results show CVC programs enabled their parent companies to acquire general and commercial AI knowledge. Specifically, CVC activities contributed in making their parent companies gain experience, hence learn, in recognizing AI technological opportunities and attractiveness, assimilating AI solutions in their boundaries, and translating AI opportunities into commercial outputs. However, CVC programs cannot substitute internal R&D efforts. They do not transfer any technological AI knowledge to their parent companies, nor do they permit the retention of AI knowledge. Those units do not directly participate to the creation of AI knowledge. Finally, AI ambiguity only has a minor impact on the relation between CVC and AI learning.

Key words: Corporate venture capital, organizational learning, inter-organizational knowledge transfer, absorptive capacity, external knowledge sources, artificial intelligence

論文概要

コーポレートベンチャーキャピタル（以下「CVC」と表記する）は、近年重要性を増している企業金融ベンチャー企業の一つである(Brigl et al., 2018)。企業はCVCプログラムを確立して、一連の戦略的および財務的目標を達成する(Basu, Wadhwa et Kotha, 2016; Maula, 2007)。企業学習はCVCの戦略的目標の一つだ。CVCプログラムは企業の外部知識源として使用できる (Dushnitsky et Lenox, 2005b)。CVCのおかげで、企業はスタートアップのような若く、革新的な起業に公正に投資することができる。CVCを通じて、企業は革新的なパートナーから学習できる潜在的な可能性がある。しかし、CVCの活動が企業の学習にどのように貢献するかについては、まだ不明だ。特に、CVCを通じて移転する知識の特徴が学習成果にどのような影響を及ぼすかについては、明確ではない。本論文はCVCと企業間学習との関係を研究することでこれらの質問に答えようとする。そのために、ケーススタディを使用して、CVCの活動が親企業の人工知能（以下「AI」と表記する）の学習にどのように貢献したかを分析する。AIは近年様々な注目が集めている、複雑で曖昧な一連の技術である。本論文では、CVCプログラム7件を含む、フランスと日本におけるAI事業を展開している企業の10件のケーススタディを紹介する。

分析結果によると、CVCプログラムにより親企業はAIに関する一般的小および商業的な知識を得ることが出来た。具体的には、CVCの活動は、親企業がAIの経験を積むために貢献したことが明らかになった。特に、CVCプログラムにより親企業はAIの技術的な機会と魅力を認識させ、AIの使用事例を同化させ、技術機会を商業的な成果に変換することも貢献した。ただし、CVCプログラムは社内の研究開発に代わるものではないことも分析結果に示されている。CVCプログラムは、技術的なAI知識を親企業に移転したり、AI知識の保持を許可したりしない。CVCはAI知識の作成に直接的に参加しない。最後に、AIの曖昧さは、CVCとAI学習の関係にわずかな影響しか与えない。

キーワード：コーポレートベンチャーキャピタル、企業学習、企業間学習における知識移転のプロセス、企業の知職吸収能力、外部知識源、人工知能

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Chapter 1 Introduction

Artificial Intelligence. This term has hit the headlines many times in the past years. Bit by bit, Artificial Intelligence has made its path into our everyday life. When typing a sentence on the internet, search engines can now guess the end of said sentence using only the first word. Language translation websites or applications powered by natural language process are becoming the norm. Personal assistants are already available on almost every smartphone around the world and can retrieve the latest weather flash in a second following a voice command. Music or video streaming services now offer songs and movies suggestions based on one personal taste. This is but a few examples on how Artificial Intelligence (hereinafter “AI”) pushed its way into our lives.

This set of technologies has slowly started to make its transition from a vast, complex research field to being widely adopted worldwide (Loukides et Lorica, 2016). And with new technological breakthroughs such as deep learning, AI has drawn growing attention in recent years. Several countries have recently launched national strategies towards the development and adoption of AI technologies (Garcia, 2019). At the same time, corporate adoption of AI solutions has steadily increased as well (Shoham *et al.*, 2018). Various industries are now being impacted by AI, forcing companies to start adopting these technologies for them to remain competitive (Bean, 2018; Davenport *et al.*, 2019; Tsutamono et Yamakawa, 2017).

The surge of AI technologies during the past decade highlights rapid technological changes companies are facing today. To compete and survive in this technological environment, firms have no choice but to adapt and innovate (Keil, Autio et George, 2008). A key factor in these adaptations and innovation efforts is knowledge. Over the past century, knowledge has become one of the most important factors of production (Drucker, 1993: 42). To create economic growth and value, companies need to develop, apply and transfer new knowledge in their operations (Liyanage *et al.*, 2009; Stehr, 2012b; Teece, 1998). In other words, organizations need to learn, as knowledge is the output of learning (Easterby-Smith et Lyles, 2011). Such organizational learning can occur at

individual and group level of analysis, but it can also take place through inter-organizational relationships (Easterby-Smith, Crossan et Nicolini, 2000).

For example, companies lacking internal capabilities to develop AI solutions could turn to external sources of knowledge, such as Corporate Venture Capital (Dushnitsky et Lenox, 2005a). Corporate venture capital (“CVC”) are corporate programs making minority equity investments into young, innovative ventures such as start-ups (Dushnitsky, 2006). In recent years, this mode of investment has skyrocketed, with more than 38 billion euros being invested through CVC around the world in 2017 (Brigl *et al.*, 2018). CVC are often used by companies to gather external knowledge, since knowledge acquisition and learning are considered important part of these programs’ objectives (Dushnitsky et Lenox, 2005b; Keil, Zahra et Maula, 2016; Maula, 2007; Wadhwa et Kotha, 2006). Transferring knowledge from ventures to parent companies could theoretically trigger organizational learning, which could in turn generate new knowledge (Argote, 2013: 149; Ingram, 2002).

Yet, evidence regarding CVC learning benefits for their parent companies is mixed (Keil *et al.*, 2008; Wadhwa et Kotha, 2006). The CVC literature has mostly focused on studying the motivations behind the establishment of CVC programs, or on studying the performance of CVCs in terms of commercial or innovative outputs (Basu, Wadhwa et Kotha, 2016). However, there has been little agreement on how, what and to which extent companies could learn from external partners using this investment mode (Dushnitsky et Lenox, 2005b: 282; Keil, Zahra et Maula, 2016). Hence, the impact of CVC on internal R&D activities and learning processes remains unknown (Keil, Zahra et Maula, 2016: 282). CVC scholars have also rarely considered knowledge characteristics as a moderator and contingent factors when studying CVC knowledge transfer (Phelps, Heidl et Wadhwa, 2012). However, transferring intricate pieces of knowledge such as AI could have an impact on CVC learning benefits.

Therefore, this paper seeks to analyze in greater detail the relationship between CVC and organizational learning, using the setting of AI technologies corporate adoption. This research seeks to address the following question: **How does CVC contribute to a company’s AI learning effort?**

It is relevant to focus on AI to analyze this research question, as AI is a set of technologies under various levels of development attracting considerable attention and investments worldwide (Burgess, 2018; Ransbotham *et al.*, 2018). CVC may therefore be used as a way to learn AI knowledge.

Three sub-questions have been devised to study this research question. The first one seeks to look into the impact of CVC on the AI learning processes of its parent company. The second sub-question focuses on analyzing the impact of AI ambiguity on the CVC AI learning. By nature, an ambiguous piece of knowledge is complex, specific and tacit (Reed et DeFillipi, 1990; Simonin, 1999). AI was considered to fit this definition. Finally, the third sub-question analyzes the moderators in the relationship between CVC activities and AI learning.

To examine the research question, this essay followed a qualitative multiple case study approach as it could provide deep insights into this situation (Cooper et Schindler, 2011: 160-183; Eisenhardt et Graebner, 2007; Gerring, 2007: 36). 11 interviews have been conducted at 10 companies, 7 of which were CVC units, in France and Japan. Studying the relationship between CVC and AI learning in those countries was deemed relevant, as France and Japan are both currently developing their AI expertise (Ministère de l'économie et des finances et Atawao Consulting, 2019; Scappaticci, 2018). Besides, CVC investments are quite common in both countries (Deloitte et Orange Digital Ventures, 2019; Riney, 2015).

This paper has been divided into seven chapters. The first chapter introduces this research, its context and its objectives. The second chapter provides a detailed literature review of CVC, organizational learning and AI. The third chapter proposes a conceptual framework to guide this essay. The fourth chapter presents this research setting, explaining the current state of AI and CVC in Japan and France. The fifth chapter is devoted to detailing this research's methodology and analysis strategy. The sixth chapter displays the data collection results and their analysis. Finally, the seventh chapter concludes this research by offering summary of the analysis results, the research contributions and limits and potential avenues for future research.

The analysis results comprise 10 propositions that emerged from the research question. The main findings could be summarized as follows.

AI learning in CVC relationships occurred mainly through knowledge transfer between ventures and parent companies. This learning was limited, as the knowledge transferred only concerned general, commercial and market AI knowledge. In these conditions, AI knowledge retention has not been observed. Potential AI knowledge creation or technological AI knowledge transfer would only occur indirectly following CVC activities by changes in the parent company's strategy. CVC activities could also secure M&A opportunities, which could lead to the parent company having access to the ventures AI technological knowledge.

CVC activities still had some impact in the kind of AI learning achieved at their parent companies. CVC programs enriched their parent companies exploratory learning process by widening the range of AI technologies and opportunities accessible to them. They also improved their parent companies transformative learning process by accelerating the assimilation of AI solutions, promoting learning in knowing when and where to use AI external knowledge. Finally, CVC taught parent companies to experiment with AI and outsource commercial and technological AI needs, facilitating exploitative learning process and fast-tracking their innovative and commercial outcomes.

AI ambiguity did not have a major impact on the relationship between CVC and AI learning, as the knowledge transferred in this investment structure was general. Ambiguity only manifested itself in the screening process of start-ups, at the exploratory learning process. Generally, intra-organizational transfer capacity, prior AI absorptive capacity and social ties moderated the relationship between CVC and AI learning.

Chapter 2 Literature review

The literature review objective is to provide a detailed representation of this research main concepts, while identifying emerging gaps. It has been divided in three sections.

Organizational learning, and especially organizations learning in AI, is this research's central theme. It is necessary to lay strong foundations in explaining what is meant by "learning" in order to accurately answer the research question. The first section therefore focuses on this concept. The goal of this section is to present the nature of knowledge, to understand what it means for an organization to learn and how organizations learn.

A second important theme relates to corporate venture capital (hereinafter "CVC"), a private equity investment mode used by companies. The second section focuses on explaining this investment method and compares it to other investment modes. It presents the link between CVC and organizational learning as analyzed by the literature.

Finally, the recent increase in CVC investments worldwide coincides with a surge in AI investments. As part of this research focuses on AI characteristics, the in and outs of this set of technology need to be clarified.

2.1 Organizational Learning

"Everything is hard before it is easy" Goethe J.W.

How can the renewed interest in AI during the past decade be explained? Part of the answer lies with the importance of knowledge in today's societies for individuals and companies alike. Though it is a difficult concept to coin, knowledge participates in the value creation process of a firm (Argote, 2013). The first subsection will describe how knowledge became a key element for organizations. Knowledge importance prompts companies to actively seek acquiring it. In other words, companies

want to learn, as it will be explained in the second subsection. However, what exactly does organizational learning imply? To what extent can a collective structure learn? The learning subprocesses will be explained in the third sub-section.

2.1.1 Knowledge

The nature of knowledge

What do we know? How do we know what we know? Being a significant idea, it is not surprising that many thinkers have studied “knowledge” throughout history. Indeed, knowledge has been an important topic in philosophy since antiquity and the first Greek philosophers (Cilliers, 2005; Drucker, 1993; Nonaka, 1994; Stehr, 2012a). Theories on the definition of knowledge and its origin are countless and various, and there is no consensus on the definition of knowledge. (Drucker, 1993: 26-27). Indeed, knowledge is a multidimensional concept with “multilayered meanings”, which comes in many forms (Nonaka, 1994). Knowledge can either be tangible or intangible: it can exist in the mind of individuals but can also be present in objects (Stehr, 2012a).

A way to capture the essence of knowledge comes from distinguishing it from related terms such as “data” and “information” (Liyanage *et al.*, 2009). Data is essentially raw information (David et Foray, 2002). For individuals, data could represent all the inputs that are processed by our five senses. Information on its hand consists of structured and formatted data sets (David et Foray, 2002). It can be regarded as a flow of data (Nonaka, 1994). Information is “passive” by nature until it is used by an individual who interprets and process said information (David et Foray, 2002).

How does information becomes knowledge? Cilliers (2005) highlights two definitions of knowledge made by different schools of thought. Positivist thinkers claim that the world can be explained in an objective way. For them, knowledge exists and is true as long as it is something rationally justified. The constructivist thinkers, on the other hand, suggest that knowledge only exists through personal and cultural perspectives. Hence knowledge never entirely objective.

The second perspective is perhaps more relevant to describe knowledge used in everyday life (Nonaka, 1994; Stehr, 2012a). For many scholars, knowledge “proves itself in action” (Drucker, 1993: 33). For the author, knowledge exists because it delivers an outcome for individuals, for societies and their economies. This capacity for action also means knowledge has to be embedded in a specific social and cultural context (Stehr, 2012a).

For Nonaka (1994), information becomes knowledge once it has been interpreted given the commitment and beliefs of the information holder. It becomes a “justified true belief”. In other words, knowledge is information that was personalized by individuals, based on facts, concepts, interpretations, observations and judgments (Alavi et Leidner, 2001). Knowledge is the capacity for an individual to make a judgment, based on the context or derived from a theory, or both (Bell, 1999, as quoted by Tsoukas et Vladimirov, 2001).

Knowledge is a “justified true belief” (Nonaka, 1994)

Knowledge characteristics

Characteristics of knowledge have long been studied by scholars. For Easterby-Smith et Lyles (2011), numerous types of knowledge are available to individuals or organizations. As highlighted by Alavi et Leidner (2001), knowledge taxonomies are important. For the authors, they shape the way we understand how organizations learn. In fact, knowledge characteristics can affect learning processes, from its creation to its transfer (Argote, 2013: 49). Tacit and explicit knowledge, famously identified by Polanyi (1966, as quoted by Nonaka, 1994), are the most widely cited characteristics of knowledge (Alavi et Leidner, 2001). However, there are other ways to understand and analyze knowledge. For clarity purposes, the main knowledge characteristics found in the literature have been summarized in table 1, shown below.

Table 1 - Knowledge characteristics

Knowledge characteristics	Source	Definition
Simple Vs. Complex	Sorenson, Rivkin et Fleming (2006) ; Simonin (1999);	A complex knowledge requires several knowledge interactions to produce a desired outcome; It is related to several interdependent technologies, resources,

	Namwoon Kim, Im et Slater (2013); Kogut et Zander (1992) ; Cilliers (2005) ; Williams (2007)	individuals. Due to complexity, organization members are not able to precisely understand all the interlinkages of a piece of knowledge (process, structure, link to other pieces of knowledge). Simple knowledge is the opposite.
Tacit Vs. Explicit	Nonaka (1994); David et Foray (2002); Kogut et Zander (1992) ; Reed et DeFillipi (1990)	Tacit knowledge is hard to formalize and communicate and is tightly linked to a specific context. It is rooted in action, commitment and involvement. Explicit knowledge is easily transmittable as it is expressed in a particular language (manuals, reports, databases, etc.). Also refer to as codifiability, or the ability to structure knowledge to easily communicate it.
Autonomous Vs. Systematic	Teece (1998)	An autonomous knowledge can be added to another without any impact. A systematic knowledge triggers modification.
Individual Vs. Collective	Ancori, Bureth et Cohendet (2000); Tsoukas et Vladimirov (2001) ; Nonaka (1994)	Knowledge is first a personal experience and is stored by individuals. Collective knowledge is shared through norms and routines among individuals.
Specific vs. Non-Specific	Reed et DeFillipi (1990); Sampler (1998); Simonin (1999)	The extent to which the acquisition or use of knowledge is limited to certain individuals or assets. It is harder to redeploy a specific knowledge for alternative uses without a loss of productive value. Specific knowledge in acquisition can only be acquired by a person with the necessary specific knowledge to acquire it. Specific knowledge in use can only be interpreted and used by people with necessary prior specific knowledge.
Observable Vs. Non-Observable	Teece (1998)	A non-observable knowledge, such as internal organizational process, can not be analysed from outside seers.

Towards knowledge societies

Prior to the 18th century, knowledge was seen as “general”, “encompassing”. Knowledge was collected with the single intent of knowing enough to navigate through life (Drucker, 1993). For the author, knowledge was neither “an ability to “do” nor a “utility”.

Yet, the current representation of knowledge is closely linked to tools, processes, products and technologies (Drucker, 1993). For the author, knowledge has become an ability, a way to “know” and “apply”. This shift in the meaning of knowledge occurred around 250 years ago, with the arrival of capitalism and the productivity revolution. It was then further amplified with the management revolution (Drucker, 1993: 42).

Today, knowledge is being applied to knowledge (Drucker, 1993: 42). It is currently being used to discover new, effective and efficient knowledge (Drucker, 1993: 42). For the author, knowledge has become the most vital factor of production with traditional “factors of production” (capital and labour) becoming secondary. For example, developed economies in search of growth do not rely solely on raw material transformation activities nor manufacturing activities (Teece, 1998). They have to develop, apply and transfer new knowledge as part of their economic activities (Teece, 1998).

As a result, many scholars argue that humans are living in “knowledge societ[ies]” today (David et Foray, 2002; Drucker, 1993; Nonaka, 1994; Stehr, 2012b). The source of economic growth or value-adding activities rely evermore on knowledge (Liyanage *et al.*, 2009; Stehr, 2012b). Societies are investing heavily on knowledge through intangible activities such as learning, research and development. (David et Foray, 2002).

Knowledge in organizations, for organizations

Why is knowledge important for companies? The past decades have seen the liberalization of markets, an increase in firms’ competition, a surge in the flow of goods and the economies’ financialization (Teece, 1998). Companies are now facing more abrupt technological complexity while at the same time experimenting rapid technological change (Keil *et al.*, 2008). One striking example of this situation would be the rapid rise of internet and its related technologies. Another one is the development of AI. In order to survive this tough technological reality and the fierce competitive landscape, companies must adapt and innovate using knowledge (Keil, Autio et George, 2008).

For a long time, companies were only viewed as being information processors (Nonaka, 1994). Organizations would operate by retrieving information at the lowest-cost possible and subsequently use it to solve the problems they would face (Ancori, Bureth et Cohendet, 2000; Teece, 1998). At that time, knowledge was not considered to be something that needed to be actively created and managed by the firm (Nonaka, 1994).

New competitive and technological landscape forced companies to modify their knowledge strategy (Teece, 1998). Those strategies changed from diminishing investments costs in knowledge into being able to “sense and seize knowledge opportunities” through knowledge (Teece, 1998).

Knowledge also came to play a more decisive role for companies as it ended up being considered a discriminator in firms’ survival (Ingham, 1997). Knowledge, created or acquired by the firm, could procure a competitive advantage through innovation, which is a process “in which the organization creates and defines problems and then actively develops new knowledge to solve them” (Nonaka, 1994). Apart from innovation, knowledge could also create value through the recombination of a firm’s asset as posited by Engel (2015). The author mentions that strategic advantage frequently results from inventive ways of extracting value from innovation, not just from the innovation itself.

Competitive advantage obtained through knowledge will erode over time, with the emergence of substitutes or new competitive threats (Lane et Lubatkin, 1998). Companies will have to develop new capabilities, or adapt their existing capabilities, to answer threats by using new or existing organizational knowledge (Andrew Inkpen, 1998; Lane et Lubatkin, 1998). As Andrew Inkpen (1998) puts it “Knowledge provides the capacity for organizational action and new knowledge provides the capacity for organizational renewal”.

2.1.2 Learning in organizations

The organizational learning research field

Numerous scholars have tried understanding the ins and outs of knowledge, given its importance for companies. From the 1990s, research has especially flourished in this field (Easterby-Smith et Lyles, 2011).

Easterby-Smith et Lyles (2011) highlight the existence of four main areas of research focusing on studying the relationship between knowledge and companies: organizational learning, learning organization, knowledge management and organizational knowledge.

The organizational learning field is “the study of the learning processes of and within organizations” (Tsang, 1997). It is important to note that the organizational learning field focuses, as its name suggest, on understanding how a firm learns through knowledge creation, transfer and retention (Easterby-Smith et Lyles, 2011). The learning organization research field centres more on grasping organization learning capacity and how to improve it, for example through organizational design (Tsang, 1997). Broadly speaking, the organizational knowledge field studies the nature of knowledge, its characteristics and differences, how it is stored and shared (Easterby-Smith et Lyles, 2011). The knowledge management field aims at “creating ways of measuring, disseminating, storing and leveraging knowledge in order to enhance organizational performance” (Easterby-Smith et Lyles, 2011). Compared with the organizational learning field, which focuses more on the process of knowledge creation, acquisition and application, the knowledge management field puts more emphasis on knowledge content (Easterby-Smith et Lyles, 2011).

Earlier, it has been mentioned that companies seek to gather knowledge as it proves to be a valuable asset to hold. In other words, organizations are trying to learn, as knowledge is the output of learning (Easterby-Smith et Lyles, 2011). In fact, learning has been recognized as required for companies to be successful in changing environments (Edmondson, 2002). Learning can be defined as “an iterative process of action and reflection, in which action is taken to produce desired outcomes” (Edmondson, 2002).

The organizational learning field provides interesting insights into the learning processes of firms (Easterby-Smith, Crossan et Nicolini, 2000). As the “the study of the learning processes of and within organizations” (Tsang, 1997), it attempts to understand the various mechanisms that lead to changes in organizational knowledge (Schulz, 2002).

Definition of Organizational Learning

The organizational learning field has attracted enormous attention from the 1990s to the point where various definitions of the construct have emerged. (Easterby-Smith et Lyles, 2011). Those

definitions stem from debate regarding the nature of individual learning (Shipton et DeFillipi, 2011). To comprehend collective learning scholars have all put the emphasis on “cognitive modelling based on theorizing at the individual level” (Shipton et DeFillipi, 2011).

For Shipton et DeFillipi (2011), discussions on the nature of individual learning enriched our comprehension of organizational learning, and at the same time made it more complex. The conceptualization of individual learning had an impact on the understanding of organizational learning as companies ultimately learn from individuals (Daniel Kim, 1993).

Figure 1 shows the different perspectives that have been considered by scholars in the individual learning theory.

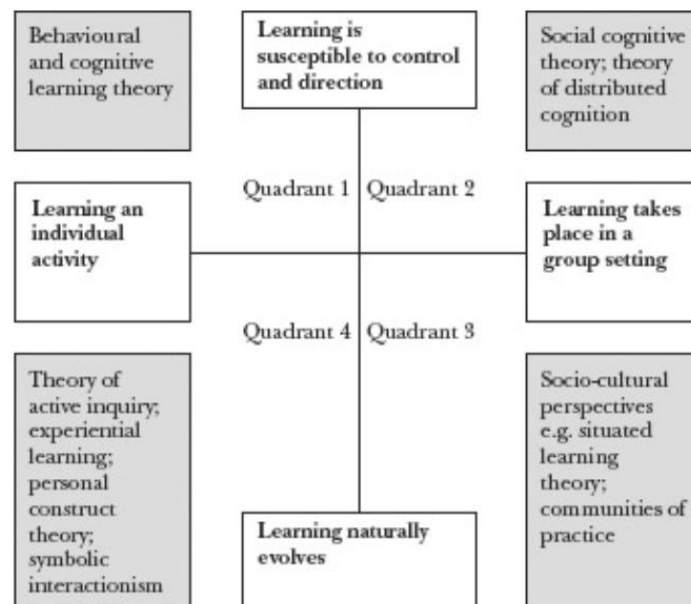


Figure 1 - The Four Quadrant Framework – (Shipton et DeFillipi, 2011)

Shipton et DeFillipi (2011) framework divides those perspectives through four quadrants. The left side of their framework explores learning as an individual activity whereas the right side explores its social nature. The top section of the framework explores a positivist view of learning whereas the bottom section considers learning through a constructivist lens.

As summarized in quadrants 1 and 4, some scholars explored how individuals interact with their environment to learn and change (Shipton et DeFillipi, 2011). They analyzed the concept of

“learning by doing” (Levitt et March, 1988), double-loop learning (Argyris, 1976), or reviewed the practice-based nature of learning (Shipton et DeFillipi, 2011).

Quadrants 2 and 3 present learning theories that consider learning to be a social activity. Learning is thought to be highly linked to the social system in which the learner belongs (Shipton et DeFillipi, 2011). Here, scholars have examined learning as a product of its environment (Huysman, 2000), as being socially constructed (Brown et Duguid, 1991) or as a process ruled by the interaction between the individual and its environment (Bandura, 1982).

As ideas on the nature of individual learning differed, various interpretations of organizational learning have emerged. For Argyris et Schön (1996: 16), organizational learning “occurs when individuals within an organization experience a problematic situation and inquire into it on the organization’s behalf”. The authors tend to pertain to the behaviourist – cognitivist view of individual learning.

At the other side of the spectrum, Brown et Duguid (1991), stress that “[organizational] learning is fostered by fostering access to and membership of the target community-of practice, not by explicating abstractions of individual practice”. For the authors, referring to a constructivist perspective, organizational learning cannot be distinguished from individual learning, it is socially constructed and distributed among communities-of-practice.

Hence, there is no consensus on the organizational learning definition. Yet, Argote (2013: 31) argues that most researchers would define organizational learning as “a change in the organization’s knowledge that occurs as a function of experience”. Organizational learning is a process that adds something to, transform or reduces organizational knowledge through “experiential learning” (Levitt et March, 1988; Schulz, 2002). In other words, companies learn when they adapt to their environment by confronting their previous experience to their context through behavioural and cognitive process.

“Organizational learning is a change in the organization’s knowledge that occurs as a function of experience” (Argote, 2013: 31)

Experience is defined “in terms of the number of task performances” (Argote, 2013: 33). For the author, this experience build-up as a company performs its tasks. Argote (2013: 33) indicates for example that the number of surgeries performed by a hospital surgical team would be a measure of experience. As pointed out by Holmqvist (2003), scholar have found experience to be present in routines, programs, operating procedures and other organizational rules. These rules and routines will adapt through time, following the firm’s experiential learning (Holmqvist, 2003). For Schulz (2002), organizations will in turn be shaped by learning processes that will combine their current and previously accumulated experience.

Organizational learning is a process that occurs through time and in a given context (Argote et Miron-Spektor, 2011). This context may be an environmental context or an organizational context (Argote, 2013: 33).

Fiol et Lyles (1985) point out that contextual factors influence the probability for an organization to learn. For example, a company’s strategy is a deciding factor for an organization to learn, as it will provide the breadth of action the latter can take (Fiol et Lyles, 1985). In the same logic, the authors mention that the organizational design will also impact organizational learning, by constraining new experiences. The environment is also decisive, as it influences the kind of experience a company will acquire (Argote, 2013: 33). At the same time, it can hinder learning in case of extreme complexity (Fiol et Lyles, 1985). The knowledge produced through learning is therefore embedded in its context, which will affect future learning for the firm (Argote, 2013: 35).

Units of Organizational Learning

In the literature, scholars have found that an organizational learning could occur at different levels of analysis, from an individual perspective to an inter-organizational perspective (Easterby-Smith, Crossan et Nicolini, 2000).

The first level of organizational learning is the individual level. Argyris et Schön (1996) assert that organizational learning is first generated by members of an organization who “have their assumptions tested through explicit collective enquiry”, i.e. the organization set of shared mental models. Individuals can learn via their own experience in an organizational context (Holmqvist, 2003). Daniel Kim (1993) mentions that individual learning is crucial for organizational learning. However, for the author not all individuals create organizational learning; it is not dependent on a specific member of the organization. In fact, some scholars established that organizational learning could not be resumed to the sum of each organization members’ learning (Argote et Miron-Spektor, 2011; Fiol et Lyles, 1985).

Scholars such as Senge (2006) and Edmondson (2002) also highlighted the importance of learning occurring at a group level. For these scholars, organizational learning also occurs in the actions of smaller communities of organization members. They argue that groups are an essential component of organizational learning, linking individuals to the organizational level. In turn, this linkage leads to learning outcomes (Edmondson, 2002). Indeed, Brown et Duguid (1991) stress that work practices get modified by “small networks called communities of practice, by sharing stories and insights in the context of doing work”. Broadly speaking, communities of practice are groups of people sharing a common interest or concern, wishing to know more or get an expertise regarding this subject, and interacting in order to fulfill this goal (Wenger, McDermott et Snyder, 2002: 4). For Wenger, McDermott et Snyder (2002), learning occurs at the group level by the interweaving of communities of practice and business process, through a process they call “multi-membership learning cycle”.

At the organizational level, learning is generated when all organizational members produce a common “social reality that is understandable in terms of their earlier experience” (Levitt et March, 1988: 327). In other words, the organization learns because its members confront their experiences

to create a shared organizational reality (Wenger et Lave, 1991). This learning can be seen in routines for example (Argote, 2013: 88). For Levitt et March (1988: 327), organizational members interact through practices, organizational stories, shared perceptions. They draw experience from such things as documents, accounts and files.

More importantly for this research, another stream of literature has focused on learning taking the form of knowledge transfer, collaborations or imitation between organizations. This stream of literature has been coined “inter-organizational learning” and is the last level of analysis for organizational learning. This level of analysis focuses on learning emerging when organizations interact with other companies (Bapuji et Crossan, 2004).

For Ingram (2002), inter-organizational learning “occurs when one organization causes a change in the capacities of another, either through experience sharing, or by somehow stimulating innovation”. For the author, this learning may be intentional or unintentional. Specifically, companies learn by producing sets of “interorganizational experiential rules” (Holmqvist, 2003). This level of analysis includes learning synergies between organizations that would not have happened if these organizations had not interacted (Larsson *et al.*, 1998).

Table 2 below summarizes the different units of organizational learning.

Table 2 - Organizational learning -Units of analysis

Unit of analysis	Learning performed
Individual	Individual learn by doing and having their assumptions tested. This learning moves to a collective level.
Group	Groups learn by interacting on a common subject through sharing stories and insights. It links the individual level to the organizational level.
Organizational	Organization learn because its members have agreed upon a common social reality, based on their previous experiences
Inter-organizational	The interaction between organizations create a change in the capacities of the receiving firm

2.1.3 Organizational learning sub-processes

The literature on organizational learning examines processes that influence and drive the organizations' ability to learn or the ability to create and modify organizational knowledge (King, 2007; Levitt et March, 1988; Schulz, 2001). In other words, how organizational learning occurs.

It happens through three interrelated processes: knowledge creation, knowledge transfer and knowledge retention (Argote, 2013: 47). While these processes are presented separately, the author stresses they are interrelated. For example, transferring knowledge between units could potentially lead to new knowledge creation.

This essay focuses mainly on the role played by CVC as a mediator in inter-organizational ties. In an inter-organizational relation such as a CVC, the core organizational learning process would first occur through knowledge transfer between one company to another. Knowledge creation or retention would be by-products of this prior knowledge transfer.

Knowledge creation

Knowledge creation is one of the first sub-processes of organizational learning. An organization first learns by producing knowledge "developed from a unit's own direct experience" (Argote, 2013: 47).

Nonaka and Takeuchi knowledge creation theory help in getting a broader understanding of this knowledge process dynamics (Ingham, 1997). Knowledge creation is a process where individual knowledge gets amplified and internalized into the organization's knowledge base (Nonaka, 1994). For the author, organizational knowledge gets created primarily as result of a continuous dialogue between explicit and tacit knowledge. This continuous dialogue between tacit and explicit knowledge has four different patterns of interaction, namely socialization, combination, externalization and internalization (Nonaka, 1994). The author's identified patterns of interaction are presented in figure 2.

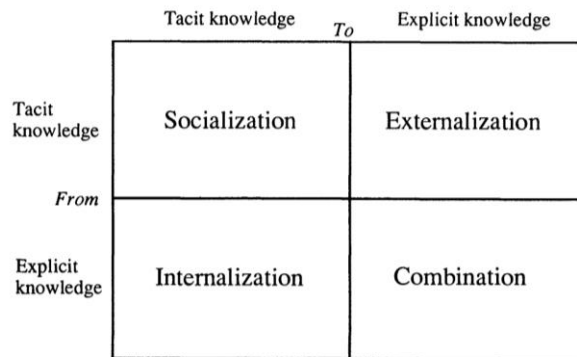


Figure 2 – Knowledge creation - (Nonaka, 1994)

“Socialization” occurs when individuals share their experiences and challenge each other “thinking processes”. Sharing experience is key to acquire tacit knowledge, according to Nonaka (1994). Hence, it is within teams or “field of interaction” that this socialization occurs. “Combination” occurs when an organization attempts to structure its explicit knowledge to create a shared base of knowledge and common practices. In turn, this explicit knowledge can create new knowledge. “Externalization” is the translation from tacit to explicit knowledge using tools such as dialectic, metaphors or analogies. In fact, these language tools allow individuals to present and better articulate their thinking processes, revealing “hidden tacit knowledge” that is arduous to communicate. Finally, “Internalization” is the pattern which is related to the notion of learning. Explicit knowledge is being acquired by individuals and become tacit, through training and practice, in a process of trials and errors.

The dynamic interactions between these four patterns contribute to knowledge creation (Nonaka, 1994). For the author, as these interactions involve more individuals and stakeholders, the organizational knowledge creation process will take the form of an upward spiral. The process will involve ever more organizational levels and knowledge holders, with specific learning processes being performed at each level (Andrew C. Inkpen et Dinur, 1998). Through these different processes and levels, knowledge gets created, shared, integrated, and justified by all the firm members (Nonaka, 1994).

Knowledge retention

The knowledge retention sub-process focuses on the storage and flowing of knowledge in an organization (Argote et Miron-Spektor, 2011). For the authors, knowledge retention has been identified as a vital element for organizational learning.

Some decades ago, knowledge was believed to persist through time. However, this idea has now disappeared (Argote, 2013: 58). The author points out that research has shown organizational knowledge declines through time if not kept “alive”. Huber (1991) mentions that learning depends on attention, “which is directed by previous learning retained in memory”.

To establish learning, to use what has been learned, companies must first retain knowledge (Huber, 1991). Argote (2013: 47) points out that some degree of knowledge retention is even required for its transfer. At the same time, the way organizational members interpret new information and experiences is influenced by organizational rules, references or cognitive maps (Huber, 1991). Those rules and references are all linked to organizational retention (Huber, 1991).

Organizational knowledge is stored through several means. Not only does it reside in individuals, knowledge can also be found in routines and procedures (Levitt et March, 1988), technologies, equipment, structure, culture and norms (Argote, 2013). Argote et Ingram (2000) call knowledge repositories “reservoirs” (from the French “réservoir” to keep for later use). Those reservoirs consist for the authors of the company’s task, tools and members. They also mention that networks existing between these reservoirs form an integral part of knowledge retention.

Several factors could endanger knowledge retention, such as not anticipating future knowledge needs, not systematically storing knowledge in repositories, not facilitating knowledge retrieval and not storing members knowledge into organizational repositories (Huber, 1991).

Knowledge transfer

Argote et Ingram (2000) define knowledge transfer as the process through which one unit of an organization is affected by another unit. Said otherwise, it is the indirect learning from the experience of another (Argote et Miron-Spektor, 2011). Van Wijk, Jansen et Lyles (2008) provide a similar definition, stating knowledge transfer is “the process through which organizational actors – teams, units, or organizations – exchange, receive or are influenced by the experience and knowledge of others”. Hence, knowledge transfer involves the sharing and acquisition of knowledge between units (Wang et Noe, 2010; Williams, 2007).

Knowledge transfer is used by organization members or companies themselves when they wish to acquire knowledge that they deem critical for new ideas development or existing ideas enhancement (Liyanage *et al.*, 2009). Van Wijk, Jansen et Lyles (2008) mention that knowledge transfer is also alternatively referred as “knowledge acquisition”, or “knowledge flow” in the literature. In organizations, transfer occurs at the individual level but also at higher levels such as group, department, division, and inter-organizational level (Argote et Ingram, 2000). Knowledge transfer is crucial at the inter-organizational learning level of analysis.

Knowledge transfer happens by using several mechanisms (Argote, 2013: 149). For example, units could communicate their knowledge orally, share explicit knowledge (documents, blueprints, descriptions), share knowledge-embedded products (technological hardware, software), move people between departments or organizations, share routines and practices, share benchmark and other “best practices”. (Argote, 2013: 149; Liyanage *et al.*, 2009).

Knowledge transfer can be observed through changes in the organization’s knowledge base, receiving units’ performance or general innovativeness (Argote et Ingram, 2000; Milagres et Burcharth, 2019; Van Wijk, Jansen et Lyles, 2008). In fact, it manifests itself when some pieces of external knowledge get integrated within the receiving unit or receiving company (Argote et Ingram, 2000; Van Wijk, Jansen et Lyles, 2008).

Challenges in knowledge transfer tend to knowledge replicability, adaptation, imitability and appropriability. Replication is the exact transfer of knowledge from one unit to another, or one

company to another (Teece, 1998; Williams, 2007). Adaptation is the goal of using knowledge transfer to modify the practices of the receiving unit (Williams, 2007). Imitation is replication, performed by a competitor (Teece, 1998). Appropriability is simply the ease of imitation (Teece, 1998).

For the author, several challenges emerge when it comes to replicating and adapting knowledge. First, one must consider the difficulty companies face to properly identify the appropriate knowledge they wish to transfer (Liyanage *et al.*, 2009; Paraponaris et Sigal, 2015). It is, for example, rather difficult to understand which routine from another unit favour a desired competence (Teece, 1998).

In addition, knowledge is a “justified true belief”, hence is a subjective representation depending on a context (Nonaka, 1994; Paraponaris et Sigal, 2015). For the receiving unit or company, knowledge must be contextualized to properly understand how it will or could be used. Otherwise the purpose of knowledge transfer will be lost, especially in the case of knowledge adaptation; no learning could be performed (Liyanage *et al.*, 2009; Williams, 2007).

Yet another challenge in replicating knowledge is the personal barriers to transfer: units, or external companies, do not necessarily have a desire to share and do not feel the wish to receive other’s knowledge as they could consider themselves the expert in a field (Paraponaris et Sigal, 2015). As explained by Liyanage *et al.* (2009), knowledge transfer process could fail following “issues of confidentiality, cultural difficulties and fear of losing competitive edge”.

Also, knowledge being transferred cannot be replicated with perfect fidelity (Teece, 1998). The knowledge receiving company or unit will sometimes have to reconstruct the portion of missing original knowledge (Sorenson, Rivkin et Fleming, 2006). These difficulties vary according to the context, such as the industry and the type of knowledge being shared (Teece, 1998).

Characteristics of knowledge can impact knowledge transferability (Szulanski, 1996). Specifically, knowledge ambiguity could hinder transferability for the author. Knowledge ambiguity, for Szulanski (1996), refers to the “lack of understanding of the logical linkages between actions and outcomes, inputs and outputs and causes and effects that are related to technological or process know-how”.

In other words, it is the uncertainty surrounding the complete understanding of the various components of a piece of knowledge and their interactions (Szulanski, 1996; Van Wijk, Jansen et Lyles, 2008).

A knowledge deemed “ambiguous”, as per its characteristics, would be harder to transfer. It may hinder knowledge transfer and assimilation in an inter-organizational relation (Xie, Wang et Zeng, 2018). Three main attributes of knowledge have been identified as sources of ambiguity in the literature (Reed et DeFillipi, 1990; Simonin, 1999; Xie, Wang et Zeng, 2018). For the authors, knowledge tacitness, complexity and specificity increase the ambiguity of a piece of knowledge. The other characteristics shown in table 1 of the literature review are not considered, as they do not have an equal impact on knowledge transferability.

At an inter-organizational level of analysis, challenges in transferring knowledge can be mitigated by the “absorptive capacity” of an organization. Absorptive capacity is a term that was first coined by Cohen and Levinthal in 1990, as an attempt to describe which characteristics made a firm more likely to learn from others. The authors’ idea is that companies need to be “prepared” in order to absorb external knowledge, by detaining prior related knowledge or having a sufficient knowledge base in an area (Wesley M. Cohen et Levinthal, 1990). Internal R&D capabilities are often necessary for companies to successfully learn from CVC (Dushnitsky, 2011). When a firm develops an expertise in a domain or a technological field, it becomes capable of assimilating external knowledge, following knowledge transfer, in similar domains and fields (or explore unrelated ones) (Díaz-Díaz et de Saá Pérez, 2014). Hence, the more absorptive the firm is, the easier it is for the latter to transfer knowledge from an external company.

For Lane, Koka et Pathak (2006), the absorptive capacity of a firm is its ability to acquire new external knowledge through three different learning processes: exploratory learning, transformative learning and exploitative learning. Exploratory learning consists in recognizing and understanding new knowledge outside the firm boundaries (Lane, Koka et Pathak, 2006; Szulanski, 1996). Transformative learning combines the access to external knowledge and its assimilation in the parent company by linking new knowledge to the company’s knowledge base (Lane, Koka et Pathak,

2006). A firm capable of transformative learning can redefine its product portfolio based on technological opportunities (Garud et Nayyar, 1994). Exploitative learning helps the firm create new knowledge and commercial outputs from the combination of the assimilated knowledge and its knowledge base (Lane, Koka et Pathak, 2006).

Hence, the absorptive capacity has an impact on the extent of knowledge being transferred between units at an inter-organizational level. Transferring knowledge has an equal impact on a firm absorptive capacity. A majority of studies have found absorptive capacity to be both an antecedent and an outcome of organizational learning (Wesley M. Cohen et Levinthal, 1990; Lane, Koka et Pathak, 2006; Veugelers, 1997; Volberda, Foss et Lyles, 2010). Said otherwise, there is a recursive relationship between learning and absorptive capacity (Lane, Koka et Pathak, 2006). As Lane, Koka et Pathak (2006) put it, “Increased learning in a particular area enhances the organization’s knowledge base in that area, which further increases its absorptive capacity and, thus, facilitates more learning in that domain”. For Lane, Koka et Pathak (2006) absorptive capacity further allows a firm to “reinforce, complement, or refocus [its] knowledge base”.

Therefore, by acquiring knowledge through knowledge transfer, an organization can increase its knowledge base, therefore enhancing its prior absorptive capacity (Volberda, Foss et Lyles, 2010). Absorptive capacity links inter-organizational transfer to organizational learning processes (Lane, Koka et Pathak, 2006; Lichtenthaler, 2011; Lichtenthaler et Lichtenthaler, 2009).

Following the organizational learning literature, learning occurs via three processes. They are summarized in the table 3, shown below.

Table 3 - Organization Learning sub-processes - (Argote, 2013)

Sub-process	Definition
Knowledge creation	The development of knowledge from a unit’s own experience
Knowledge retention	The storage and flow of knowledge in the organizational knowledge base
Knowledge transfer	The indirect development of knowledge from another unit’s experience

2.2 Corporate Venture Capital

「虎穴に入らずんば虎子を得ず」 “*Nothing ventured, nothing gained*”

Companies need to react to their uncertain environment through change and adaptation using knowledge (Keil, Autio et George, 2008). However, companies may not have enough capabilities to develop their own knowledge, to learn on their own. One solution would be for companies to turn to external sources of knowledge as a mean to overcome these challenges (Dushnitsky et Lenox, 2005a). In other words, to focus on inter-organizational learning, as defined in a previous section. The following part introduces corporate venture capital as a method to acquire knowledge for a firm.

The first subsection will explain why firms resort to external sources of knowledge. The following subsection will then focus on providing the current state of knowledge regarding CVC, from an organizational perspective. The last subsection will present CVC from an entrepreneurial perspective.

2.2.1 External sources of knowledge

As mentioned previously, organizations seek to gather knowledge for various reasons. One reason is the status knowledge has gradually taken in the past century in our societies (Drucker, 1993; Liyanage *et al.*, 2009; Stehr, 2012b). Since a few past decades, companies have also started facing a more competitive landscape while at the same time experimenting rapid technological change (Keil *et al.*, 2008). In order to survive this tough technological reality, companies must adapt, change and innovate to remain competitive (Keil, Autio et George, 2008). Therefore, learning is required for companies to be successful in this changing environment (Edmondson, 2002).

For a long time efforts toward change, adaptation and innovation was the work of in-house R&D departments (Keil, Autio et George, 2008). Change and innovation were only viewed as a necessity to adapt to new realities, not as a matter of firms' survival (Engel, 2015).

Today, there is no longer a need for companies to justify investments made to create and gather knowledge (Díaz-Díaz et de Saá Pérez, 2014). The real question is rather to know how companies

can invest efficiently to succeed in changing, adapting, innovation (Díaz-Díaz et de Saá Pérez, 2014). Companies are under pressure of both exploiting and exploring knowledge continuously, while improving the rate of success of both initiatives (Wadhwa et Kotha, 2006). However the costs and risks of investing internally in R&D are high, due in part to technological and research complexity (Vivas et Barge-Gil, 2015). According to Keil, Autio et George (2008), such complexity, risk and cost of investing in R&D entail that companies have to recognize they might not possess sufficient capabilities to sustain a research effort by themselves.

For this reason, companies lacking capabilities can turn to “external” knowledge sources (Díaz-Díaz et de Saá Pérez, 2014). Dushnitsky et Lenox (2005a) infer for example that companies will use external knowledge sources when their marginal contribution to the companies’ innovative output is higher than the companies own internal R&D sources. Several factors influence the use of external knowledge sources. Vivas et Barge-Gil (2015) posit that large, R&D-intensive companies are more likely to invest in external knowledge ventures. At the same time, they also mention that the industry level of technological complexity and cost obstacles are other factors that are determinants for the use of external ventures.

To select and manage external knowledge sources, companies create “external corporate venturing” projects (Keil, 2004). This term refers to activities created and undertaken by companies to support organizational learning on one hand, the development of new capabilities on the other (Keil, 2004). Owing to the knowledge origin (suppliers, customers, competitors, public institution) but also projects structure (alliances, joint ventures, venture capital), there is a large variety of venturing projects (Van de Vrande, 2013). Some of these venturing projects are displayed on the following figure 3.

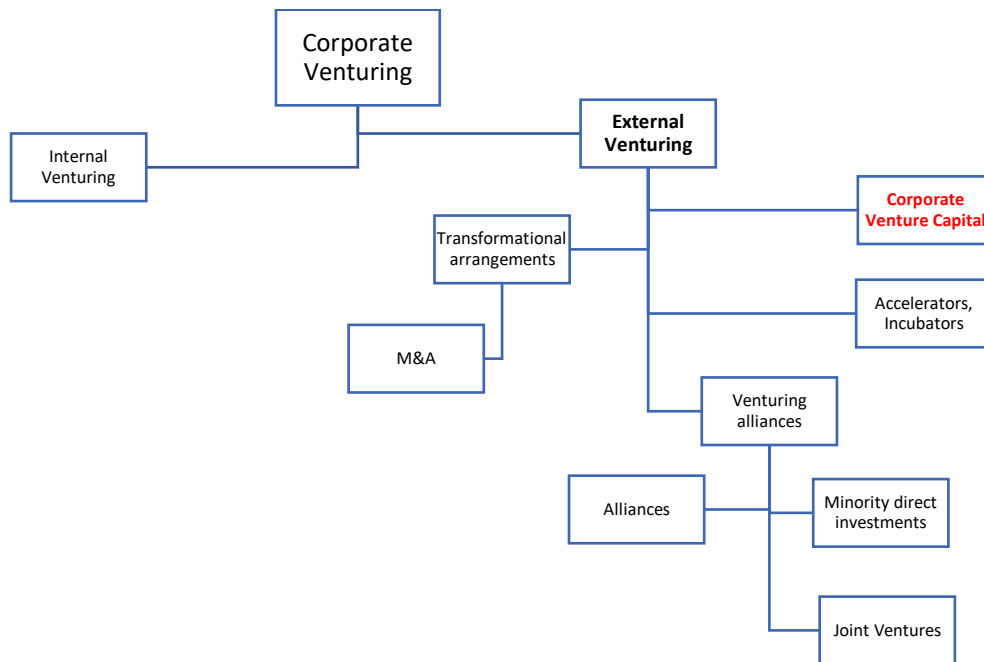


Figure 3 - Venturing projects modes– adapted from Maula (2007)

One way to classify these different external knowledge sources is to rank them along the “continuum between arms-length transactions and [...] fully integrated solution” (Van de Vrande, Vanhaverbeke et Duysters, 2009). The authors posit that alliances, due to their flexible structure, are an example of arms-length transaction. On the contrary, mergers and acquisitions (hereinafter “M&A) are deeply integrated solutions. CVC on their end are relatively flexible solutions for corporations (Van de Vrande, Vanhaverbeke et Duysters, 2009). They are located on the arms-length transactions side of the continuum (Van de Vrande, Vanhaverbeke et Duysters, 2009).

Most established companies do not limit their venturing activities to a single governance mode when trying to acquire external knowledge (Van de Vrande, Vanhaverbeke et Duysters, 2009). However, using multiple external knowledge sources could bear negative effects. Capitalizing on several investment modes results in a decrease of the marginal benefits of using external knowledge sources (Fleming et Sorenson, 2001). To mitigate this risk, managers need to find venturing solutions that would properly answer their needs. It is relevant to observe which governance modes are likely to be used under which circumstances (Van de Vrande, 2013).

For Van de Vrande, Vanhaverbeke et Duysters (2009), finding suitable venturing projects depends on the type of uncertainty a firm has to handle. According to uncertainty comes in two forms: exogenous uncertainty and endogenous uncertainty. Exogenous uncertainty, otherwise known as external uncertainty, relates to a type of uncertainty that is unaffected by the firm's own action, such as the "environmental turbulence" and "technological newness". Endogenous uncertainty, or relational uncertainty, is embedded in inter-organizational relationships. It can be reduced by companies' actions such as experiencing prior cooperation experiences with partners or working with the latter into getting a similar knowledge basis (Van de Vrande, Vanhaverbeke et Duysters, 2009).

Under exogenous uncertainty, Van de Vrande, Vanhaverbeke et Duysters (2009) have found that arms-length transactions such as alliances and CVC are adequate solutions. These transactions allow firms to make small learning investments under unpredictable conditions, while remaining flexible (Van de Vrande, Vanhaverbeke et Duysters, 2009). Keil *et al.* (2008) reached a similar conclusion, arguing that CVC investments are the most favoured mode of sourcing for exploration projects, followed by alliances and joint ventures. Under endogenous uncertainty, a large technological distance between two firms increases the chance of using CVC programs. However, prior cooperation between firms increase the chance of minority holdings or joint ventures (Van de Vrande, Vanhaverbeke et Duysters, 2009).

Modes of external venturing

Hence, when selecting a governance mode, companies must evaluate the level of uncertainty they are facing. The following section defines in greater details the different external knowledge governance modes presented in figure 3.

M&A is defined by Dushnitsky (2011) as "the combination of two independent companies into one large company or [the] acquisition [of one by another]". By combining two organizations' activities, M&A provides a channel for companies to absorb various knowledge into their operations (Keil *et al.*, 2008). Nevertheless, M&A can be difficult to put in place for a company, as it has to choose

between preserving its partner and preserving its autonomy (Phanish, Harbir et Maurizio, 2006). M&A is rigid investment option with high degrees of financial commitments where companies cannot easily exit their investment agreements (Van de Vrande, Vanhaverbeke et Duysters, 2009). As such, in a period of environment turbulence and technology newness, M&A is not favoured by companies (Van de Vrande, Vanhaverbeke et Duysters, 2009). This result has also been observed by Dushnitsky (2011), who found mixed results for M&A on gaining access to new technologies. A few factors push companies into undergoing M&A investments. First, technological proximity between firms increase the probability of M&A investments (Chondrakis, 2016). Second, spin-offs created by former employees are more likely to be part of an M&A investment than other types of firms (Andersson et Xiao, 2016).

Joint ventures require the creation of a separate entity jointly owned by different companies (Keil *et al.*, 2008). Like M&A, joint ventures are integrated investment solutions with huge financial commitment put in place toward a new entity establishment (Van de Vrande, Vanhaverbeke et Duysters, 2009). For Keil *et al.* (2008), joint ventures have a positive relationship with companies innovative performance. However, like M&A, joint ventures are relatively rigid investment options when it comes to exploring new ideas while they also entail additional financial risk (Van de Vrande, Vanhaverbeke et Duysters, 2009). Hence, technological newness has a negative effect on the probability for companies to use joint ventures. However, prior cooperation between firms has a positive effect in the probability to use joint ventures investments (Van de Vrande, Vanhaverbeke et Duysters, 2009).

Strategic alliances could be defined as the “voluntary arrangement between independent firms to share and exchange resources in order to develop products, services and technologies” (Dushnitsky, 2011). Alliances allow partners to share cost, help market entry or develop joint project (Dushnitsky, 2011). Alliances are flexible considering they resemble market transactions, with low levels of control between each partner and few hierarchical controls (Van de Vrande, Vanhaverbeke et Duysters, 2009). Besides, partners in an alliance preserve their autonomy over their tasks, making

alliances a true hybrid between markets and hierarchical relationships (Kapoor et Lee, 2013). Alliances are an interesting source of external knowledge for companies, as they facilitate access to partners' knowledge and could be used in co-creation projects (Keil *et al.*, 2008). Alliances also facilitate knowledge sharing and coordination between associates by making communication channels and shared codes available to all partners (Kapoor et Lee, 2013). Eisenhardt et Schoonhoven (1996) have found that alliances were more likely to form when companies have strategic needs (firms with a vulnerable position in a competitive environment) or social opportunities (large corporations led by well-connected management teams).

A corporate accelerator is a program that supports a start-up growth through education, mentoring and occasionally financing (Goldstein, Lehmann et Prax, 2015; Hathaway, 2016). Companies can also provide office space or resources for the start-ups to grow, even using their network to help that growth (Goldstein, Lehmann et Prax, 2015). Corporate incubators also follow the same objective, making a start-up grow from its seed stage to an early development stage. There are, however, some clear differences between incubators and accelerators (Susan Cohen, 2013). Incubators follow start-ups during a period of time usually ranging from one to five years (Susan Cohen, 2013). On the other hand, start-ups take part in accelerators for a limited period of time, lasting on average three months (Susan Cohen, 2013; Hathaway, 2016). Accelerators also accept start-ups in a cohort, while incubators usually accept start-up year long (Susan Cohen, 2013). For the author, accelerators tend to provide more advice and mentoring to start-ups and less financial support than incubator. Accelerator and incubators are beneficial for companies, as they provide access to early-stage innovation (Goldstein, Lehmann et Prax, 2015). Those flexible structures allow for companies to experiment and access external knowledge, within the framework of an organization (Goldstein, Lehmann et Prax, 2015).

To define corporate venture capital, it is first relevant to define "venture capital" (hereinafter "VC"). VC firms are a type of private equity firms investing in "entrepreneurial ventures" or young firms with high growth potential in the hope of achieving a positive and substantial financial gain (Pahnke,

Katila et Eisenhardt, 2015). Compared to private equity firms, VC companies rarely acquire start-ups. In the same logic, CVC are minority equity investments made into young firms, such as start-ups (Dushnitsky, 2006). CVC programs seek strategic and financial benefits for their “parent company” (the investing firm) by investing in young firms (Pahnke, Katila et Eisenhardt, 2015). Dushnitsky (2006) highlights three features that differentiate CVC from other equity investments. First, although financial returns are important in a CVC project, it is not the only consideration. Second, the investment is managed via funded ventures, called CVC programs, that are privately held by the parent corporation. Finally, parent companies receive a minority equity stake in the firms it invested in. Dushnitsky (2006) further specifies that CVC is not a form of non-equity-based organizational relationship like alliances. They are distinct from alliances as there is no hierarchical relationships with the funded start-up company (Basu, Wadhwa et Kotha, 2016: 203). In addition, the authors mention that CVC investments almost always involve several investors to each round of financing. Dushnitsky (2006) also highlight that CVC programs are not internal corporate venturing projects, spin-offs nor spin-outs.

Table 4 below reviews the main information regarding external knowledge governance mode.

Table 4 - Main external knowledge governance mode

External Knowledge Governance Mode	Definition	Location on continuum (Van de Vrande, Vanhaverbeke et Duysters, 2009)	Type of Investment
Mergers and Acquisition	The combination of two companies into one large companies or the acquisition of one by the other (Dushnitsky, 2011)	Fully-integrated solution	Equity investment
Joint Ventures	Creation of a separate entity jointly owned by different companies (Keil <i>et al.</i> , 2008)	Integrated solution	Equity investment
Alliances	Voluntary arrangement between independent firms to share and exchange resources in order to develop products, services and technologies (Dushnitsky, 2011)	Arm-length relationship	Non-equity investment

Accelerators and Incubators	Program or organization that support start-ups growth through mentoring, resource distribution, education and sometimes financing (Susan Cohen, 2013; Hathaway, 2016)	Arm-length relationship	Non-equity investment / could lead to equity investment
CVC	Minority equity investments made into young firms, such as start-ups (Dushnitsky, 2006)	Arm-length relationship	Equity investment

To summarize, external sources of knowledge can be used simultaneously by organizations to answer their knowledge needs (Van de Vrande, 2013). Yet, using numerous external knowledge sources could be counterproductive as relying on multiple venturing mode could decrease the marginal benefits made by investing in each of these various sources (Fleming et Sorenson, 2001). It may be more appealing for managers to focus on external knowledge sources that match their companies' level of uncertainty.

Faced with a changing technological landscape, many firms are now choosing CVC to accelerate their learning efforts (Brigl *et al.*, 2018). As specified by Van de Vrande, Vanhaverbeke et Duysters (2009), CVC is relevant during time of exogenous uncertainty. AI, representative of this technological newness and rapid change, makes it interesting to analyze CVC as an external source of knowledge for companies.

2.2.2 Defining CVC

A renewed interest in CVC

CVC is a cyclic investment mode having experienced more than three “waves” (increased number of CVC investments in a short period of time) since the 1960s (Dushnitsky, 2011). The number of CVC investments performed globally has grown again in the past years. In 2011, CVC accounted for more than 11% of all VC investments amounts worldwide (Lerner, 2013). In 2012, this percentage rose to 20% and in 2017 to 26% (Brigl *et al.*, 2018). Between 2012 and 2017, the total amount of global VC investments skyrocketed from 50 billion euros to 147 billion (Brigl *et al.*, 2018). Therefore,

CVC investments experience a compound annual growth rate (“CAGR”) of around 31 % (Brigl *et al.*, 2018). Figure 4 below depicts this sharp increase in both VC and CVC investments.

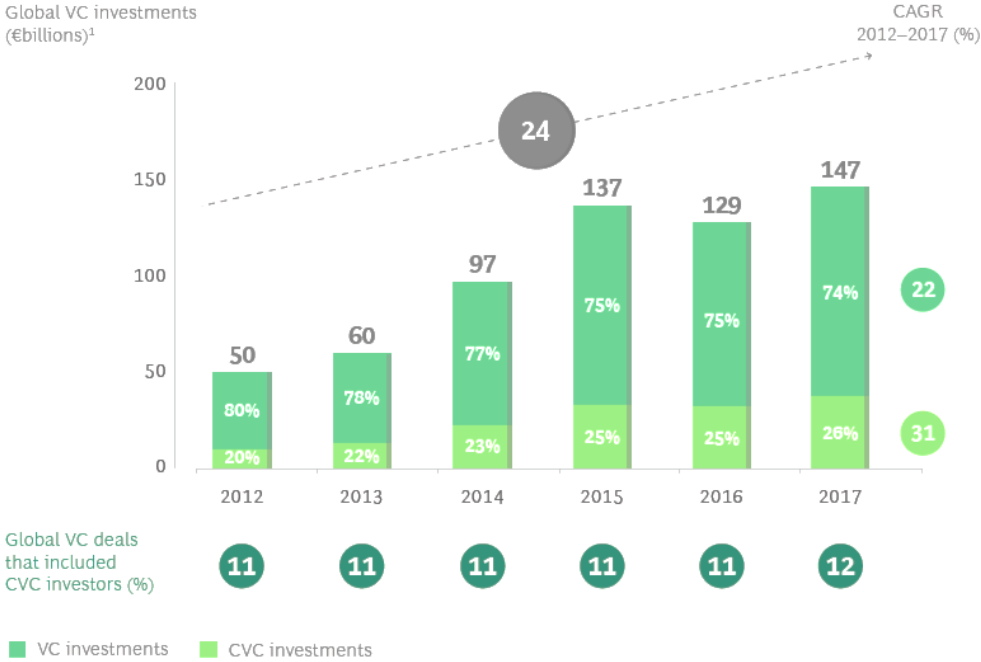


Figure 4 - CVC growth in the global VC investment - Brigl *et al.* (2018)

In the past, organizations would perform CVC investments to increase their financial performance (Brigl *et al.*, 2018). However, they would step back at the first signs of economic downturn (Brigl *et al.*, 2018). Nowadays, scholars have noticed CVC programs tend to last longer. Their life spans extend to four years or more, compared to the earlier waves limited one to two years’ life spans (Dushnitsky, 2011; Lerner, 2013). Today, apart from financial returns CVC is used by leaders to find solution to digitization (Brigl *et al.*, 2018; Lerner, 2013).

Two broad perspectives have been used by scholars to study CVC (Basu, Wadhwa et Kotha, 2016). The first perspective examined CVC from the corporate investor point of view. The second perspective addressed CVC issues from an entrepreneurial perspective. The main points of the first perspective are presented in the following sections.

CVC programs' objectives

A large part of the CVC literature has focused on explaining the motivations for establishing CVC activities (Basu, Wadhwa et Kotha, 2016: 205). According to Dushnitsky (2006), companies usually chase a double objective by starting CVC programs. Their first objective is financial. It is realized by achieving a capital appreciation through financial operations such as trade sales. For example, a CVC program invest in an entrepreneurial venture, and leaves once a favourable financial exit is made possible (Dushnitsky, 2006).

Yet motivations behind creating CVCs are mostly strategic (Dushnitsky, 2006). Scholars identified various strategic objectives (Basu, Wadhwa et Kotha, 2016: 205). One of these strategic objectives is the exploration of new technologies (Dushnitsky, 2006; Pahnke, Katila et Eisenhardt, 2015). The emergence of new technologies is said to be a precursor to CVC investments, whereas companies are seeking to develop such technologies (Dushnitsky, 2006). Other strategic objectives could include the exposure to entrepreneurial spirit, novel corporate culture ideas, environment scanning, ecosystem building or the opportunity to enter foreign markets, among others (Basu, Wadhwa et Kotha, 2016: 205-206; Dushnitsky, 2006). For clarity purposes, the different motivations for the establishment of CVC have been summarized in table 5, adapted from Maula (2007)'s research.

Table 5 - CVC objectives - (Maula, 2007)

CVC Objectives	Examples
Financial Objectives	
Financial Gains	Financial Return
Strategic Objectives	
Learning	
Market-Level Learning	Radar-like identification of, monitoring of, and exposure to new technologies, markets and business models
Venture Learning	External R&D
Indirect Learning	Change corporate culture, train junior management, learn about venture capital, improve internal venturing, Complementary contacts
Option Building	

Option to acquire companies	Identify and assess potential acquisition targets
Option to enter new markets	Accelerate market entry, option to expand
Leveraging	
Leveraging own technologies and platform	Increase demand for technology and products, shape markets, steer standard development, support development of new application for products
Leveraging own complementary resources	Add new products to existing distribution channels, utilize excess plant, space, time & people

Allen et Hevert (2007) report that the scientific community is currently divided on the weight and importance to give to strategic and financial objectives. Some scholars stress the importance of tangible financial results in providing funding and senior management support (Allen et Hevert, 2007). They also point out the skepticism that can surround investments made primarily on unmeasured strategic benefits. Advocates of strategic objectives point out that stressing financial returns could potentially prematurely end programs (Allen et Hevert, 2007). Besides, emphasizing on financial objectives may lead to a less diverse CVC programs portfolio, bringing in fewer opportunities for learning strategic knowledge (Allen et Hevert, 2007).

Managing CVC programs

Scholars have studied how CVC programs can be organized, from their structure, resources, systems, procedures or policies (Dushnitsky, 2011; Keil, Autio et George, 2008; Keil, Zahra et Maula, 2016: 271) . The interaction between start-ups or ventures and the parent company is mediated by CVC programs. This intermediation is what differentiates minority investments from CVC investment (Maula, 2007).

Dushnitsky (2006) has identified three main varieties of CVC structures. The “direct investment” are operating business units of the parent company managing CVC activities on their own. Next, the “wholly owned subsidiaries” are separate organizational structure set up to pursue CVC activities on behalf of the parent company. Finally, the “dedicated funds” are a structure type where an independent VC co-manage a firm’s CVC activity. Separating the CVC unit from the rest of the company can reduce potential conflicts. However it could also sever the links the CVC unit maintain

with parent company, making it difficult to communicate and diffuse potential knowledge or opportunities (Keil, Zahra et Maula, 2016: 277-278)

Dushnitsky (2006) highlights two important dimensions of CVC programs autonomy. The first dimension relates to capital allocation. Some parent companies prefer to fund their CVC programs upfront while others provide the funding ad hoc. In other words, availability of capital is a moderator in providing complete autonomy to the CVC program. The second-dimension concerns decision autonomy. Some CVC programs have complete freedom to make and exit investments while others would be subject to corporate review Dushnitsky (2006).

Personnel's compensation is the third part of CVC management activities. Dushnitsky (2006) highlights the necessity to provide incentives to CVC managers for them to remain in the programs. Working in pairs with external, dynamic and appealing ventures could provide motivations for managers to leave CVC programs. Hence, the author observes the growing propensity of CVC programs providing "high-power incentives" to their CVC managers.

Outcomes of CVC programs

An important part of the CVC literature focuses on CVC outcomes, specifically on their performance (Basu, Wadhwa et Kotha, 2016: 210). Scholars have analyzed how CVCs activities participate to their parent companies' value creation (Basu, Wadhwa et Kotha, 2016: 210).

Dushnitsky (2006) reported mixed evidence regarding the economic performance of CVC programs. This situation is first explained by the difficulty to evaluate economic performance. In fact, no measure makes consensus in the literature according to Dushnitsky (2006). For example, Engel (2015) mention that near-term financial returns are of little relevance for most companies. For the author, the principal measure of CVC economic performance should not be how much it provides, but how much it will enhance companies' operation, sales and profitability.

Allen et Hevert (2007) published a paper in which they tried to give insights on the economic gains of CVC for parent companies. The authors examined the CVC activities of 90 U.S. IT firms, by using CVC programs internal rate of return (hereinafter "IRR"). Their study shows that 39% of programs had IRRs exceeding their parents' cost of capital. A total of 44% of program had economically

significant impacts on their parents (either positive or negative). Among larger programs, 33% had economically significant positive impacts and 36% negative. Those numbers go down to 16% that have economically significant positive impacts and 4% negative for smaller programs.

Hence, results from Allen et Hevert (2007) highlight the mixed evidence of the economic performance of CVC program. In another study, Dushnitsky et Lenox (2006) found that CVC program only enhanced the shareholder returns if investors pursued both strategic and financial objectives.

CVC innovative performance and its impact on parent company has also been widely studied by scholars. First, Dushnitsky et Lenox (2005b) found strong evidence that greater firm investments in start-ups lead to increase in patenting rate for its parent company. The authors proposed that exposure to novel technologies increases the likelihood for parent companies to create breakthrough innovations, leading to higher patents citation levels. Keil *et al.* (2008) also found evidence that CVC investments had a positive correlation with growth in innovative performance. In fact, CVC activity enables companies to experiment new technologies outside their boundaries (Keil *et al.*, 2008). For the authors, it allows companies to access and understand more easily socially embedded knowledge. A reason for this innovative performance could be found in the role of CVC investments as a channel for knowledge spillovers as identified by Wadhwa, Phelps et Kotha (2016). The authors also mention that synergies created between parent company and ventures could increase their innovation rate.

Learning through CVC

The CVC literature focused primarily either on the motivation behind establishing a CVC, or on the outcomes of CVC for its parent company (Basu, Phelps et Kotha, 2016). Yet, some scholars have also been giving some attention to the link between CVC and organizational learning. The literature focused on understanding the learning processes impacted by CVC relationships when it happened and how.

As depicted by Maula (2007) and other scholars, learning is an important strategic objective for firms engaged in CVC activities. Scholars have written widely about the opportunities CVC programs could

provide for organizational learning. CVC has been recognized as a way to discover and experiment on novel technologies, to change business practices or culture, to understand markets (Chesbrough, 2002; Dushnitsky et Lenox, 2005b; Maula, 2007). It is thought that CVC can have a positive effect on its explorative or exploitative learning, through activities such as search, experimentation, risk taking, refinement and implementation of strategic actions (Keil, Zahra et Maula, 2016: 265-266).

Theoretically, CVC could have an impact on learning: this investment structure enables companies to develop strong relationships with their portfolio companies (Keil, Zahra et Maula, 2016: 264). CVC programs have a relatively deep access to their portfolio companies' technology and business model, despite having a limited control on the start-ups (Keil, Zahra et Maula, 2016: 264). CVC activity enables parent company "to observe their technological skills and understand their goals, resources and business models" (Keil, Zahra et Maula, 2016: 264).

This activity could prove crucial for companies, as start-ups could control pieces of new technology the parent company may not have (Dushnitsky et Lenox, 2005b; Keil, Zahra et Maula, 2016: 264). It is relevant to mention that it still is unclear in the literature what type of knowledge gets transferred between external partners and receiving companies (Volberda, Foss et Lyles, 2010).

CVC differ from other venturing projects regarding "who learns" (Keil, Zahra et Maula, 2016: 264). The CVC unit is the link between its parent company, including the different business units and its top management, and the ventures where it invests. Hence, learning would happen throughout the interaction between these three structures according to Keil, Zahra et Maula (2016: 264).

Dushnitsky et Lenox (2005b) described three ways companies could learn from their CVC, "when" they could learn. The first learning channel occurs when CVC programs are selecting a venture through due diligence processes, as CVC programs are active in carefully selecting their investment partners (Dushnitsky, 2006). The second learning channel is realized post investment, through monitoring activities. Monitoring activities can be performed by holding board seats (2/3 of programs have a board seat; Dushnitsky, 2006) or detaining observer rights to the entrepreneurial venture (Keil, Autio et George, 2008). Keil, Autio et George (2008) add that monitoring activities could also take the form of common projects between the parent company and entrepreneurial

ventures. Finally, ventures failure acts as a third channel providing insight on technologies' potential and market unattractiveness.

Some scholars in the CVC literature have studied "how" parent companies could theoretically learn from their CVC programs. Parent companies could learn thanks to the knowledge transfer between the ventures and the parent company (Keil, 2004). For Keil (2004), through their CVCs, parent companies need to retrieve knowledge from the ventures, transfer it back, and make the knowledge their own. CVC knowledge transfer is close to Liyanage *et al.* (2009) approach to knowledge transfer, which the authors define as the "identification of (accessible) knowledge that already exists, its acquisition and subsequent application of this knowledge to develop new ideas or enhance the existing ideas to make a process/action faster, better or safer than they would have otherwise been".

Keil (2004) named this process "acquisitive learning", earlier defined by Zahra, Nielsen et Bogner (1999) as "occurring when a firm acquires and internalizes knowledge, that pre-exists externally to its boundaries". He also highlights the importance of learning from experience, or learning-by-doing, in CVC relationship, which could be linked to the knowledge creation process (Keil, 2004).

The challenge for companies is to internalize new knowledge, those new practices. Indeed, investments do not automatically lead to organizational learning and learning is not a synonym of capability creation (Keil, 2004; Keil, Zahra et Maula, 2016: 279). Knowledge receiving units need to adapt this new knowledge to their organizational context and cognitive frameworks, to hope achieving new capability formation (Keil, Autio et George, 2008; Liyanage *et al.*, 2009).

Keil, Autio et George (2008) highlight that "the transfer of a contextualized knowledge across fields of practice is inherently difficult". As mentioned in the knowledge transfer section, to integrate knowledge efficiently, one needs to know its originating context as well as its receiving context (Liyanage *et al.*, 2009). For example, knowledge about novel technologies can be fragmented and could become ambiguous if related to rival technologies (Keil, Zahra et Maula, 2016: 279).

Scholars have identified several factors that can help overcome these challenges. First, Wadhwa, Phelps et Kotha (2016) mention that the nature of interactions between parent company, CVC program and ventures has a deep impact on knowledge transfer. Indeed, trust greatly facilitates

organizational knowledge (Lee, Kim et Jang, 2015). There are two other integration factors for Keil (2004). Knowledge articulation and knowledge codification aim at capturing lessons from past cases of CVC through experimentation learning. Knowledge articulation is related to creating routines on how to conduct external CVC activities (practices, routines) to make knowledge explicit in the organization, while knowledge codification's goal is to create a common language that supports learning from experience (rules, procedures).

Hence, CVC has been identified in the literature as having potential learning benefits for a parent company. As shown by several scholars, new knowledge needs to be integrated, to be "acquired" into the firm own knowledge base. Only then can it trigger a change in the capacities of the parent company (Ingram, 2002).

Yet, there has only been mixed evidence that CVC provides any learning benefits for its parent company (Keil *et al.*, 2008; Keil, Zahra et Maula, 2016: 260; Wadhwa et Kotha, 2006). When compared to other external sources of knowledge, scholars found CVC programs could produce qualitatively different learning outcomes (Keil, Zahra et Maula, 2016: 260). These outcomes depend on the type of investment (Keil *et al.*, 2008). They would also vary depending on the number of investments a CVC program is undertaking (Wadhwa et Kotha, 2006).

Learning benefits also differed according to the investment sector or the type of industry invested in (Dushnitsky et Lenox, 2005b). For example, companies will invest more in sectors with weak intellectual properties, as it provides them a greater access to knowledge (Dushnitsky et Lenox, 2005a). Learning benefits will be greater if the start-up activities are somewhat related to a parent company activity. Dushnitsky et Lenox (2005a) specify that firm will be keener in selecting ventures with complementary assets to their operations.

CVC learning benefits in the literature is mostly measured by its observable outcomes. Authors, such as Dushnitsky et Lenox (2005a) or Schildt, Keil et Maula (2012), rely on patenting amounts or R&D expenditures to measure changes in learning at a parent company. The line between learning outcomes and innovative outcomes is therefore thin, whereas learning and innovation are different concepts. It is worth mentioning that measuring learning proves to be a difficult task (Argote et

Miron-Spektor, 2011). However, no measure perfectly grasp the complexity of learning processes according to Argote et Miron-Spektor (2011). Hence, understanding learning benefits of CVC remains an open question to this date, especially its impact on knowledge creation, retention and transfer (Keil, Zahra et Maula, 2016: 282).

According to the literature, CVC could potentially have learning benefits for its parent company. But there is no reliable evidence that CVC activities bring learning benefits for parent companies. On the other hand, the CVC literature did not accurately measure or determine the impact of CVC on learning processes. Another issue in the literature is that studies do not precisely detail what knowledge is being transferred between partners (Volberda, Foss et Lyles, 2010). In addition, knowledge characteristics are rarely identified as contingent factor in the CVC literature, whereas they could impact knowledge transfer, hence learning (Phelps, Heidl et Wadhwa, 2012; Reed et DeFillipi, 1990; Szulanski, 1996). Knowledge ambiguity could for example hinder knowledge transferability (Simonin, 1999; Szulanski, 1996)

Hence, several questions regarding CVC learning benefits remain open, as mentioned by Keil, Zahra et Maula (2016: 282). The authors call for more research to understand the relationship between CVC and organizational learning. They highlight gaps in the literature in understanding how CVC impacts the receiving firm capacity to further create, retain and transfer knowledge, how it influences internal R&D activities as well as the organization's absorptive capacity.

Taken together, the CVC literature shows that CVC is a way for companies to harness new, external knowledge. If some firms use CVC primarily for financial returns, most companies use this equity-based investment strategically sometimes with the intent of learning. There is still a need for more research on the impact of CVC on organizational learning, as its benefits still remain obscure to this date (Keil, Zahra et Maula, 2016: 282).

Yet, CVC may be an adequate form of harnessing AI knowledge for companies, as AI technologies are a new, complex technology that could prove difficult to study in firms' R&D departments alone. In linking the understanding of organizational learning and CVC, it is also relevant to get a clear picture on one of these research main themes: artificial intelligence.

2.3 Artificial Intelligence

“By far the greatest danger of Artificial Intelligence is that people conclude too early that they understand it” - Eliezer Yudkowsky

What exactly is AI? Many people interact with “AI” regularly, hear about it periodically. Yet it is possible that they may not understand the term properly. In fact, AI points to several technologies and takes its roots in several scientific and human science fields. It is particularly significant for executives to get an understanding of AI, as it is said to be a part of the next digital revolution (Morikawa, 2016). This part will focus on defining the term Artificial Intelligence, explaining the reasons behind the recent interest in AI technologies. It has been divided into two sections. The first one deals with explaining the origin of AI and its recent development. The second section will describe the current impact AI has on organizations and societies.

The definition and explanation offered hereinafter do not have the purpose to detail the numerous theories and science research behind AI. Rather, they portray an overview of the AI field. Knowing the different technologies of AI should not necessarily imply grasping the science underlying AI. Furthermore, it should be pointed out that the subsequent section will not focus on the ethical and deontological challenges the AI technologies present, such as moral status of machines or machine intentionality to name a few.

2.3.1 What Intelligence?

There have been several attempts at finding a common definition for AI, yet none reached a consensus (Loukides et Lorica, 2016; McCarthy, 2007). The most encompassing definition would be the following one: “AI is the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-

making, and translation between languages” (Oxford English Dictionary). To put it in other words, essentially, AI is a group of different technologies aiming to replicate human intelligence. It is closely related to cognition, its underlying processes often trying to mimic the human brain. Thus, to introduce Artificial Intelligence, it is first relevant to understand the antecedents and outcomes of human intelligence.

Contrary to what one might think, it is arduous to characterize intelligence. As Sternberg (2012) highlights it, several authors and researchers have analyzed intelligence throughout history and came to interpret it in different ways. Russel et Norvig (2010) also agree that “intelligence” can be defined in various manners. From the idea in ancient Greece that wisdom and virtue were discriminator in making something or someone intelligent (Plato and Aristotle, as quoted by Robinson, 1994), this concept came to be described in the Middle Ages as a way one reacts to its environment and creates cognitive abstraction to represent things (Saint Thomas Aquinas, as quoted by Robinson, 1994). According to Robinson (1994), modern schools of thought such as the rationalist (Descartes, Leibniz) and the empiricist (Locke, Hume)) also coined intelligence in different ways. Despite these various points of view regarding Intelligence, Sternberg (2012) would define the term as follows: “Intelligence is one’s ability to learn from experience and to adapt to, shape, and select environments.”

Why is it necessary to define intelligence? Because, at the heart of AI lies the assumption that a machine can perform the same tasks in terms of reason and thought as a human being. Hobbes was one of the first philosophers to back the idea that “thinking” could be understood in terms of computational operations (symbolic reasoning). This idea was then endorsed by other thinkers such as Descartes, Pascal, Spinoza and Leibniz. Hence, if thinking can be reduced to computational operations, it implies that a non-human entity can perform intellectual reasoning.

Indeed, AI is the attempt at building computing machines embodying intelligence processes (Schank, 1994). This explains why defining AI proves difficult: what AI is and will be is complex to describe, as humans do not even have a complete understanding of their own intelligence (Loukides et Lorica, 2016).

Processes of intelligence have been decrypted and applied to machines as part of the attempt to create an AI (McCarthy, 2007). To mimic these processes, AI took its roots in different branches of science, from mathematics to neuroscience through psychology, philosophy and computer engineering (Russel et Norvig, 2010). Yet, AI cannot perfectly duplicate to date human intelligence: it is not yet possible to say which computational procedures to call “intelligent” (McCarthy, 2007).

A renown debate around this idea of AI “intelligence” is the “Chinese Room”, proposed by John Searle. An AI has been trained to understand Chinese. By using Chinese characters as inputs, it can process the information and present other characters as output. John Searle (as quoted by Robert, 1992) questions the AI “Intelligence”. Has the machine indeed understood Chinese, or has it simply emulated the ability to comprehend Chinese? To put it in other words, Searle differentiates a “strong” AI, which can think by itself and has a “mind”, from a “weak” AI who would only act as if it has a mind (Burgess, 2018). To achieve a strong AI would denote that a machine has the ability to sense and learn from its environment, reason, imagine, express and act on the latter (Greenwald, 2018).

Hence, in the same way human intelligence cannot be clearly defined, AI is still complex to grasp. Labelling something “intelligent” depends on what is expected of that intelligence (Loukides et Lorica, 2016). If an AI was replicating human intelligence itself, it would be considered a “strong” AI. It would be able to frame question itself, formulate and answer that question without any exterior input, just as a human would do (Schank, 1994). In view of all that has been mentioned so far, one may suppose that AI today can only act as a “weak” AI.

From its start after World War II, AI research has seen many significant progress and breakthrough (Burgess, 2018). Nonetheless, this field has suffered from overinflated expectations during the last decades, in part because the government and corporate sphere alike expected AI to achieve the same intelligence levels as humans (see Annex 1). AI, a futuristic technology, did not live up to those expectations, due to the discipline’s complexity and cost. Yet, Burgess (2018) considers that AI usage could spread across society during this new AI boom. AI is now capable of outperforming humans in many tasks. AI capabilities have greatly improved during the past decade thanks to the appearance of big data, the decrease in storage cost and faster processing and computing power (Burgess, 2018; Ministère de l'économie et des finances et Atawao Consulting, 2019).

AI technologies

The term “AI” is often getting mixed with terms such as machine learning (hereinafter “ML”), Big Data and others (Kaplan et Haenlein, 2018). Due to this misperception, it is puzzling to understand how AI could be applied in organizations and how it could benefit them (Burgess, 2018).

AI tries to recreate human learning mechanisms. Those mechanisms involve reasoning on inputs using knowledge classification (abduction and correction operations) to plan an action (Burgess, 2018). Recreating those processes proves difficult. As a result, the AI research field has evolved in many different directions and field of studies. As research went into different directions, it became more complex to get a complete understanding of the AI technologies. According to McCarthy (2007) AI has twelve branches of study, from pattern recognition to common sense knowledge and reasoning. The following figure from Felden, Krüger et De Meyer (2017) shows some of the different AI sub-technologies. AI technologies cover a system’s ability to perceive, to think (or self-learn) and to act on its environment (Kaplan et Haenlein, 2018).

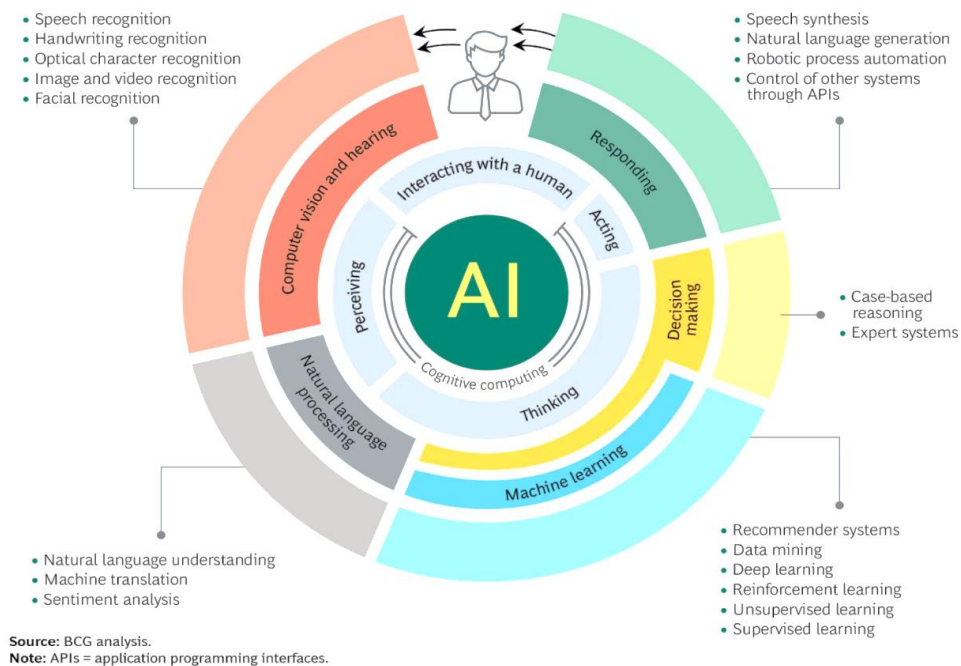


Figure 5 - AI Domains, retrieved from Felden, Krüger et De Meyer (2017)

It is crucial to distinguish AI from its related technologies. Specifically, AI is often confused with ML, those terms being used interchangeably (Marr, 2016). Indeed, ML has been the main reason for the AI surge in the past decades (Marr, 2016). It enables AI systems to automatically improve their performance by self-learning (Grosz *et al.*, 2016). Yet, ML is but a part of AI. AI is broader than ML as it also covers a system's ability to perceive data and use it as inputs (Natural Language, image/speech recognition) and the ability to act on its environment based on what he learned from its input (Kaplan et Haenlein, 2018).

A first set of AI technologies processes deal with perception. AI captures new information through technologies such as computer vision and hearing. This branch of AI relies on multiple sensors to perform such things such as computer vision (automatic image and video captioning) and focuses on labelling this new information (Grosz *et al.*, 2016). Categorizing data is important as it allows to find patterns in clusters of information. For machines, labelling new information proves difficult and requires a huge volume of training data and computing power (Grosz *et al.*, 2016).

A second set of AI technologies deal with machine thinking processes. Thinking processes gained much recognition in the AI field thanks to the invention of ML. For a machine, ML consists in retrieving data, processing it and interpreting it to produce an output (Hideki et Takashi, 2017). It is the ability for a machine to learn from manually characterized data sets. This ability is enhanced from the machine accumulating experience from multiple data sets (Scappaticci, 2018). To perform well, a machine would have to be trained with huge amounts of data to ensure it labels new inputs correctly. Machine learning systems are currently used to interpret information, may it be to identify objects in images, transcribe speech, select relevant results of search, etc. (LeCun, Bengio et Hinton, 2015). Deep learning further enhanced ML by allowing machines to compose with multiple levels of interpretation. Deep learning consists in organizing layers of artificial neurons to create a neural network. This neural network can learn data representation with different levels of abstraction by performing what is then called a "Deep Learning" (LeCun, Bengio et Hinton, 2015). Each layer of artificial neurons can identify a set of features that is then sent to the next layer in the network (Skilton et Hovsepian, 2018).

Other thinking process would be Natural Language Understanding (hereinafter NLU), optimization and prediction. NLU acts as a translator between humans and machines (Tokunaga, 2017). Natural

language interfaces such as Siri (Apple) or Cortana (Microsoft) are representative of such NLU. Optimization's main characteristic is that AI is given a goal to achieve, something to be reasoned upon (Burgess, 2018). The AI must achieve the optimum sequence to reach the final goal, given the initial states and existing limits it is provided. This ability can be used in decision-making situations. In prediction processes, AI tries to match a new piece of information into an already identified and labelled group using historical data (Burgess, 2018). For example, when applying for a credit loan, AI could match a customer's information (salary, age, spending, past financial history) and match it to similar client profile to verify the latter solvency (Burgess, 2018).

Once the AI has perceived and thought over its data, it needs to act following decision-making processes. Using the AI technologies described above, one means of action can be found in the form of cognitive robots, or in the form of robotic process automation. Cognitive robotics can be considered the physical embodiment of AI (Burgess, 2018). Using inputs from different types of sensor, robots determine the most appropriate response or action according to their function. These robots include, but are not limited to, autonomous vehicles (driverless cars and trucks), manufacturing robots and service robots. Next in order, the Robotic Process Automation (hereinafter "RPA") describes a type of software replacing transactional, rule-based works (Burgess, 2018). Example of such rule-based works can include employee recruitment, invoice processing and payment, IT service desk request, etc. RPA at its basic level then utilizes technology to replace the series of human actions required to complete each rule-based work (using simple process mapping tools).

AI technologies are known to be complex. There are several reasons to this complexity. Some AI technologies require complex algorithms that are difficult to create (Burgard, 2018). An algorithm required for self-driving cars for example needs to compose with a large set of variables to overcome environmental threats. Performance of AI algorithms are dependent the quality of data being used: data needs to be representative of the problem to solve (Ministère de l'économie et des finances et Atawao Consulting, 2019). In addition, AI's decision-making process can be hard to understand (Dengel, 2018). Once datasets have been provided as inputs into the AI, no human intervention will be required for the AI to provide an output. In particular, the deep-learning technology decision-making process is quite nebulous, making it almost impossible for humans to understand what the

machine thinking process was (Dengel, 2018; Ministère de l'économie et des finances et Atawao Consulting, 2019). As well, there are but a few specialists of AI technologies worldwide. For example, Burgard (2018) mentioned that in 2016, there were only around 3,000 advanced mathematical experts around the world capable of programming algorithms for self-driving cars.

A company willing to learn and implement AI solution to automate its processes would require data that accurately represents its environment, an expertise to model algorithms, an expertise to define AI use and an expertise in interpreting AI results (Ministère de l'économie et des finances et Atawao Consulting, 2019). Today, although the different AI technologies are still being improved, they are already having an impact on societies and on companies.

2.3.2 AI's current impact

As the last AI winter faded, as huge technological advances emerged, a new AI boom has appeared (Tsutamoto et Yamakawa, 2017). AI is now making its transition from a research field to the early stages of corporate adoption (Loukides et Lorica, 2016). Many executives recognized that AI technologies could be used in several industries, and could increase efficiency, profits and savings (Tsutamoto et Yamakawa, 2017).

Compared to the previous boom, AI faces higher social hopes, due to the high visibility it receives (Bean, 2018). There are strong expectations for AI to trigger innovations in economies and societies alike (Tsutamoto et Yamakawa, 2017). Bean (2018) mentions that this decade can see the start of companies benefitting from investing in AI. Ransbotham *et al.* (2018) posit that most companies expect AI to initiate a business model change in the next five years. Hence, the intention to use AI at companies has increased in many companies during the last years (Tsutamoto et Yamakawa, 2017).

AI enables two functions: a function to help decision-making, and an autonomous decision-making function (Ministère de l'économie et des finances et Atawao Consulting, 2019). Organizations could use AI for different purposes, such as enhancing customer service (revenue generation and

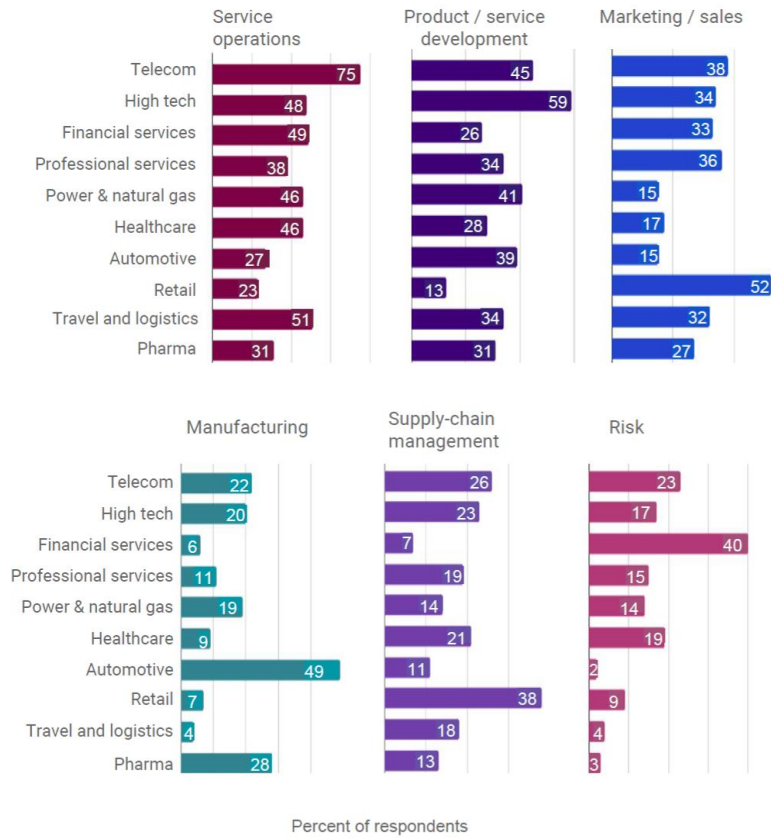
customer satisfaction through RPA for example), optimizing processes (cost reduction, cost avoidance and compliance) and helping decision-making (generating insights for risk mitigation, loss mitigation and revenue leakage mitigation) (Burgess, 2018).

Bean (2018) analyzed the benefits companies obtained from their AI investments. He found AI initiatives provided investing companies with more accurate decision-making via advanced analytics with a 69% success rate. Those companies also reduced expenses (with a 60,9% success rate), accelerated time-to-market for new products and services (54,1% success rate) and improved customer service (53,4% success rate) thanks to their AI investments. Nevertheless, only 27,3% of executives stated successful monetization of AI initiatives in their organizations (Bean, 2018).

In a worldwide survey, Bean (2018) found that 97,2% of executives questioned reported investing in AI initiatives in their respective companies. Only 12,7% of those executives mentioned the investment to be superior to half a billion US dollars (USD). Ransbotham *et al.* (2018) did a similar survey on the usage of AI in organizations. They found that 18% of all organizations surveyed could be considered AI pioneers, both understanding and having adopted AI in their business models. Thirty-three percent were investigators, understanding AI but not deploying any AI initiatives at this point. Sixteen percent were experimenters, launching AI initiatives without any prior knowledge of the technology. Only 34% of all companies were “passives”, having no comprehension nor adoption of AI. Shoham *et al.* (2018) analyzed the different rate of companies’ AI adoption across the world. They found that, despite recent increase in AI investments, true adoption of AI by companies was still relatively low around the globe, with few variations across the different geographical zones.

Shoham *et al.* (2018) noticed AI adoption also depended on the activity sector companies were operating in. The authors mention that “organizations tend to incorporate AI capabilities in functions that provide the most value within their industry”. This difference is shown in the following figure, which displays the percentage of firms that have adopted or acquired AI capabilities within “a particular business function” as of 2018 (worldwide survey, 2135 respondents each representing their company).

AI adoption by industry and function (2018)
 Source: McKinsey & Company



Note: The size of each bar is relative to the industries within each function; Telecom: N = 77; High tech: N = 215; Financial services: N = 306; Professional services: N = 221; Electric power and natural gas: N = 54; Healthcare systems and services: N = 67; Automotive and assembly: N = 120; Retail: N = 46; Travel, transport, and logistics: N = 55; Pharma and medical products: N = 65.

Figure 6 - AI adoption: Industry and Function (Shoham et al., 2018)

The majority of companies surveyed by Bean reported they invested in AI because they needed to develop such solutions to compete in an increasingly disruptive period (Bean, 2018). However, investing in and launching AI initiatives is complex due to numerous challenges as previously mentioned. For one, AI feeds on a huge quantity of data. Hence, companies need to have access to centralized data lakes, manage a company-wide data governance and must get access to quality data for their AI to be precise (Ransbotham et al., 2018). On the other hand, companies need to create a business case for AI before adopting it. Research in AI are currently ahead of business application and implementing an AI solution often equals experimenting directly with the

technology (Ransbotham *et al.*, 2018). The solution might be to scale down AI initiatives, wherever AI solutions might prove useful (Ransbotham *et al.*, 2018). Applying AI through the whole organization might prove counterproductive. Scaling it down to departments could, on the other hand, prove useful. At a corporate level, an AI strategy must be put in place to ease the technology implementation by having a clear roadmap and targets to reach (Ransbotham *et al.*, 2018).

Tsutamono et Yamakawa (2017) report that various industries can already use AI. The automotive industry already benefits from AI, using technology such as speech recognition, speech-to text synthesis, vehicle information and communication systems, adaptive cruise control and early stages of autonomous driving. The transportation industry can already use AI enhance vehicle information and communication systems, navigation system, collision avoidance and mitigation system, acceleration sensor, etc. The environment industry can use advance life cycle management AI to analyze resource circulation for instance (Tsutamono et Yamakawa, 2017). In the health care industry, AI is used to help diagnose patients. In the finance industry, it is used to perform market analysis or risk evaluation (Ministère de l'économie et des finances et Atawao Consulting, 2019). The list of applications goes on with AI use cases in other industries such as agriculture, energy, finance, electronics.

Thanks to the technological progress made in its many underlying research fields, companies have started integrating AI in their operations. While AI technologies cannot yet perform at a “strong” AI level, they can already replace and outperform humans in different tasks. Nowadays, AI already has different applications in various sectors of the economy. Companies can already benefit from AI solutions given that they try understanding the technology and the efforts required to exploit it before implementing the latter.

Literature review summary

The literature review objective was to present the current state of research regarding organizational learning, CVC and AI. These terms have all been defined and described in the previous parts. The literature review helped understand why companies would revert to external knowledge sources to adapt and change when their internal efforts limited their organizational learning. CVC has been portrayed as an investment mode companies increasingly utilize. For scholars, CVC could participate to a company's learning effort, although evidence regarding this relationship is mixed (Keil *et al.*, 2008; Keil, Zahra et Maula, 2016: 260; Wadhwa et Kotha, 2006).

Various authors point out that the various kind of interorganizational relationships might bear different results when it comes to organizational learning (Argote, 2013: 149; Ingram, 2002; Zheng Jane Zhao et Anand, 2013). Yet, few studies have thoroughly analyzed CVC learning processes. It is therefore difficult to understand precisely how, what, and to which extent companies learn in this investment mode (Dushnitsky et Lenox, 2005b). Keil, Zahra et Maula (2016: 282) point out that more research is required to understand how CVC activities affect internal R&D activities and how CVC could impact the receiving firm absorptive capacity, hence how CVC influences organizational learning. The type of knowledge transferred between ventures and parent companies through CVC needs also be clarified (Volberda, Foss et Lyles, 2010)

In addition, when scholars studied the learning benefits of CVC activities they assumed that knowledge transfer between start-ups, CVC and parent company was mostly moderated by firm variables (Phelps, Heidl et Wadhwa, 2012). Phelps, Heidl et Wadhwa (2012) highlight that other factor such as knowledge characteristics are rarely studied as a contingent factor in the literature. Studies show knowledge characteristics influence inter-organizational knowledge transfer relationships in alliances and joint venture (Reed et DeFillipi, 1990; Simonin, 1999; Szulanski, 1996). Yet, such studies remain scarce in the CVC literature. An intricate and ambiguous knowledge such as AI may hinder the potential learning a company could make through its CVC unit.

Considering the gaps identified in the literature review, the following research question has been developed: **How do CVC activities contribute to a company's AI learning effort?**

Chapter 3 Conceptual framework

The framework's purpose proposed below aims to guide this research by providing additional details to the research question. The conceptual framework is divided as follows. First, the theoretical background of the research is presented. Then, the research's sub-questions are detailed. Finally, a conceptual framework model is proposed.

3.1 Theoretical background

To analyze the link between CVC and organizational learning, this research grounds itself in the knowledge-based view of the firm ("KBV") and in the open innovation model. Those theories help explain the structures and behaviours of companies in this research context, as theories of firms are "conceptualizations and models of business enterprises" (Grant, 1996).

The KBV is an outgrowth of the resource-based view of the firm ("RBV") (Grant, 1996). The RBV is a theory of the firm trying to explain the origin of competitiveness. It does so by examining the link between a firm's internal characteristics and its performance (Barney, 1991). According to this theory, firms can sustain a competitive advantage by detaining resources (such as assets, processes, attributes) that are valuable, rare, imperfectly imitable and have no equivalent substitutes (Barney, 1991).

In the KBV, knowledge is seen as the most important resource a company can detain (Grant, 1996). In this theory, firms repositories of knowledge (Grant, 1996). For the author, organizations exist as a result of the market inability to transfer or integrate knowledge. Grant et Baden-Fuller (1995) posit that it is impossible to have "arms-length transfer of tacit knowledge" in the market. Tacit knowledge is stored by individuals, cannot be codified and is thus not transferable (Grant et Baden-Fuller, 1995). For Grant (1996), firms were thus created to be repositories of knowledge. In other words, firms can generate conditions under which individuals can integrate their knowledge, while markets cannot. Kogut et Zander (1992) share the same perspective regarding the nature of the firm. For the authors, organizations act as "social communities", transforming individual knowledge and

social expertise into valuable outcomes. Organizational knowledge is therefore socially constructed. Companies create a “common” knowledge by organizing their human resources (Kogut et Zander, 1992).

Knowledge is considered to be the key resource for a company in regard to its value-added contribution to the firm (Grant et Baden-Fuller, 1995). Knowledge is crucial for the production of goods and services of a company (Grant, 1996). In fact, producing a good or service would require that several different specialized pieces of knowledge get integrated to produce an output (Grant et Baden-Fuller, 1995). In the KBV, knowledge can procure a competitive advantage to a firm by being valuable, rare and imperfectly imitable (Barney, 1991; Grant, 1996). A firm competitiveness would depend on its ability to create, transfer and organize knowledge (Kogut et Zander, 1992). Therefore, on its capacity to learn.

This research also considers that innovation, able to procure a competitive advantage to companies, may be the result of the interaction of a firm with its environment, i.e. that the firm operates in “open innovation”. Open innovation is defined as the “the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively”(Chesbrough et Bogers, 2014). Chesbrough (2003) developed the concept of open innovation after observing that innovation at companies resembled more an open system rather than an integrated system relying on internal R&D.

The central idea of the open innovation paradigm is that an organization cannot innovate optimally by itself. Rather, its competitiveness relies on its ability to collaborate with other actors, to acquire external ideas and resources (Dahlander et Gann, 2010). The open innovation paradigm allows us to consider that company interact deliberately with their environment in order to sustain their innovation efforts (Chesbrough, 2003; Lichtenthaler, 2011).

There are two main modes of open innovation according to Dahlander et Gann (2010). Inbound open innovation allows an organization to learn new knowledge by letting external knowledge flow into its boundaries. On the other hand, outbound open innovation occurs when a firm consider

another actor to be in a better position to further develop and commercialize its proprietary knowledge.

By opening up their innovation process through inbound open innovation (or outside-in process), companies facilitate their acquisition of knowledge from external sources (Lichtenthaler, 2011). In turn, the acquisition of knowledge from external sources might sustain the learning effort of a company through knowledge transfer, retention or creation, as described in the literature review. Inbound open innovation could also explain how companies may explore, transform and exploit this external knowledge (Lichtenthaler, 2011; Lichtenthaler et Lichtenthaler, 2009).

CVC is a tool of open innovation as it helps gather external sources of knowledge. Companies engaged in CVC can be considered following an inbound open innovation scheme, wanting to acquire new, external pieces of knowledge from the interaction of their CVC programs with external partners. CVC are highly related to innovation. Studies from Dushnitsky et Lenox (2005b) have shown for example that CVC activities lead to higher patenting outcomes for a firm. Hence, it is reasonable to consider firms engaged in CVC activities to use open innovation.

3.2 Research sub-questions

How do CVC activities contribute to a company's AI learning effort?

Three sub-questions have been derived from this research question to study it as accurately as possible.

First sub-question

The first sub-question remains, of course, to understand whether CVC programs can facilitate the way parent companies learn about AI and understand what is learned through CVCs. To answer this issue, the following sub-question was thus developed:

1- How do CVC activities impact parent companies' AI learning processes?

Measuring learning

This essay first explores how CVC programs contribute to the AI learning processes of a firm. As previously stated in the literature review, scholars have highlighted the complexity of measuring learning in organizations (Argote et Miron-Spektor, 2011). As defined before, organizational learning would be defined for most scholars as a change in the organization's knowledge that occurs as a function of experience (Argote, 2013: 31).

Some scholars have tried measuring organizational learning by analyzing changes in the cognition of organizations' members, or by considering changes in a firm's economic or innovative performance (Argote, 2013: 31). Others, such as Dushnitsky et Lenox (2005b) for example, measured learning by studying the patenting outcomes of firms investing in CVC. However, none of these measuring methods perfectly grasp learning processes according to Argote et Miron-Spektor (2011). Therefore, how can the impact of CVC on a company AI learning be measured?

To alleviate this problem, Argote (2013) suggests the best approach would be to measure organizational learning according to the research question and empirical context.

This research focuses on CVC activities, which are situated at the inter-organizational level of analysis of organizational learning. It aims at understanding how learning processes get impacted or mediated by CVC activities. CVC units act as intermediaries between ventures and parent companies in open innovation knowledge relationships. Two sets of AI learning processes could be impacted: the organizational learning subprocesses and the absorptive capacity learning processes.

Organizational learning sub-processes

Measuring organizational learning through changes in learning subprocesses could inform us *how* CVC activities modify their parent companies' knowledge base. CVC programs may first directly impact knowledge transfer (experience-sharing between units) between start-ups and parent companies as they are a link between the two. Subsequently, CVC programs could alter processes such as knowledge creation (units creating knowledge on their own) or retention (storing knowledge for future use) thanks to previously transferred knowledge.

It is highly relevant to study these sub-processes in this research as they indicate how learning occurs for a firm, and how CVC activities could have altered this learning (King, 2007; Levitt et March, 1988; Schulz, 2001). The framework fits both the KBV, as knowledge is the outcome of learning (Easterby-Smith et Lyles, 2011), and the open innovation paradigm, as CVC acts as a tool for outside-in knowledge transfer.

Yet, organizational learning subprocesses do not inform on what kind of learning is taking place at the parent company as a result of CVC programs. They only inform on how organizational learning happens at a company (through knowledge transfer, creation or retention management).

Absorptive capacity learning processes

To understand *what* kind of learning CVC activities facilitate, it is interesting to look into the concept of absorptive capacity, which was introduced previously. Absorptive capacity allows firms to acquire knowledge by making them better able to value, assimilate and apply external knowledge (George *et al.*, 2001: 279; Keil, Zahra et Maula, 2016).

In detail, firms with absorptive capacity get better at acquiring knowledge through processes such as exploratory, transformative and exploitative learning processes (Lane, Koka et Pathak, 2006). As explained earlier, exploratory learning consists in recognizing and understanding new knowledge outside the firm boundaries (Lane, Koka et Pathak, 2006; Szulanski, 1996). Transformative learning combines the access to external knowledge and its assimilation in the parent company by linking new knowledge to the company's knowledge base (Lane, Koka et Pathak, 2006). Exploitative learning helps the firm create new knowledge or commercial outputs from the combination of previously assimilated knowledge and its knowledge base (Lane, Koka et Pathak, 2006). These learning processes are all dependant on the prior knowledge base of the firm (Wesley M. Cohen et Levinthal, 1990; Lane, Koka et Pathak, 2006; Volberda, Foss et Lyles, 2010).

If absorptive capacity is considered an antecedent of organizational learning, it is also its outcome (Wesley M. Cohen et Levinthal, 1990; Lane, Koka et Pathak, 2006; Veugelers, 1997; Volberda, Foss et Lyles, 2010). At the inter-organizational level of analysis, knowledge transfer from an external partner could increase the parent company absorptive capacity, i.e. its knowledge base, which could promote further organizational learning (Lane, Koka et Pathak, 2006). Hence, the acquisition of

external knowledge could enhance the absorptive capacity learning processes, opening the path for more learning (Lane, Koka et Pathak, 2006). CVC activities may alter the absorptive capacity learning processes, demonstrating what kind of learning was triggered through CVC programs.

To our knowledge, no previous study has analyzed the impact of CVC on its parent company absorptive capacity learning processes. Keil, Zahra et Maula (2016) in fact highlighted the lack of research regarding the influence of CVC on a firm absorptive capacity.

Studying the changes in the absorptive capacity's learning processes to measure organizational learning at an inter-organizational level is relevant: Lane, Koka et Pathak (2006) have highlighted the strong link existing in the literature between inter-organizational learning and absorptive capacity. Absorptive capacity processes are also linked to the organizational learning processes (Lane, Koka et Pathak, 2006; Lichtenthaler et Lichtenthaler, 2009). Studying absorptive capacity learning processes fits with the KBV theory, as absorptive capacity is "key to developing and increasing a firm's knowledge base", leading to potential competitive advantage (Volberda, Foss et Lyles, 2010). Studying how CVC affects its parent company absorptive capacity learning processes also suits the open innovation paradigm as these processes help understand how a firm manages its inbound knowledge flow through exploration, transformation and exploitation (Lichtenthaler, 2011; Lichtenthaler et Lichtenthaler, 2009).

To summarize, a way to measure how CVC impacts its parent company AI learning processes would be to understand whether CVC programs enhance AI learning at their parent companies through knowledge transfer, creation or retention. CVC programs and parent companies might learn from ventures how to understand AI knowledge, how to integrate it and how to exploit it. Those learnings may be transferred from ventures to parent companies. In an open innovation paradigm, firms manage external knowledge and ideas, and may wish to acquire them. By transferring knowledge, a CVC might enhance the absorptive capacity learning process of its parent company. By facilitating the integration of external knowledge, CVC may also alter knowledge retention at its parent company. Finally, by learning external knowledge and means to exploit it, CVC programs may enhance their parent company AI knowledge creation process.

Figure 7, below, shows the link between the organizational learning sub-processes and the absorptive capacity learning processes.

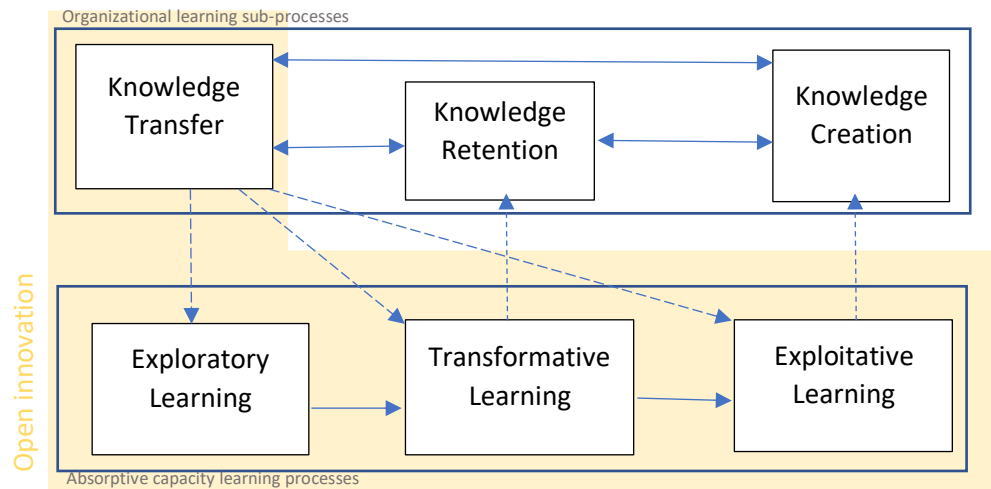


Figure 7 – Learning processes used to measure AI learning

Second sub-question

For parent companies to learn, for learning processes to be modified, knowledge must first be shared and acquired from start-ups to CVCs. CVC units' members would need to transfer knowledge back to their parent company or facilitate knowledge transfer between ventures and their parent company. Without a relevant knowledge transfer, there may not be any learning taking place in the CVC relationship.

Closely related to the concept of knowledge transfer is the notion of knowledge transferability. For Simonin (1999), knowledge transferability relies on how easy it is to transport, understand and assimilate knowledge. Szulanski (1996) refers to knowledge transferability as “internal stickiness”, describing the difficulty of transferring knowledge within a firm. This transferability is linked in part to knowledge characteristics, as the latter have an impact on knowledge accumulation, retention and diffusion across firm boundaries (Argote, McEvily et Reagans, 2003; Szulanski, 1996).

The second sub-question focuses on understanding whether the characteristics and transferability of AI influenced learning processes occurring through CVC units:

2- Does AI ambiguity have an impact on the organizational learning processes?

An encompassing characteristic of knowledge, “ambiguity”, as defined previously in the literature review, is linked to knowledge transferability (Simonin, 1999). It has been found to hinder knowledge transfer (Reed et DeFillipi, 1990; Simonin, 1999; Xie, Wang et Zeng, 2018). The tacitness, complexity and specificity increase the ambiguity of a piece of knowledge (Reed et DeFillipi, 1990; Simonin, 1999; Xie, Wang et Zeng, 2018).

One may consider AI as an ambiguous piece of knowledge. AI is composed of several sets of technologies (NLU, ML, etc.) and demands various resources (such as data, computational power, algorithms, etc.) to function. Researching and developing this set of technologies could require the input of several individuals as their AI competences can spread across several fields (computation, cognition, mathematics, logic, etc.). A company would need to understand the different knowledge interlinkages of AI technologies to be able to absorb them (Garud & Nayar, 1994, as quoted by Lane, Koka et Pathak, 2006). This set of technologies is known to be complex, as mentioned earlier. This complexity can affect the extent to which a company can understand external AI knowledge (Simonin, 1999). Besides, the ability to understand and apply AI knowledge could be labelled a tacit knowledge, as it represents a “know-how”. Nevertheless, it is worth mentioning that information regarding AI technologies (which could be referred as “know-what”, such as theories) can be still be found in manuals or on the internet. Yet, translating information and facts to implement AI might prove difficult for firms. Only a few individuals around the world have a complete knowledge of AI (Burgard, 2018). In addition, acquiring AI would require companies to already have a relative amount of AI knowledge to adapt it so that it can fit specific application within the company’s boundaries. When using AI technologies, organization members would also need to have enough AI knowledge to understand how it works and could benefit their activities. Therefore, AI could also be defined as a specific knowledge.

Third sub-question

Finally, the last sub-question simply focuses on understanding what the moderators in the relationship between CVC activities and AI learning are:

3- What are the moderators in the relationship between CVC and a company's AI learning effort?

After a comprehensive literature review Easterby-Smith, Lyles et Tsang (2008) proposed a framework of factors influencing inter-organizational learning. This research builds on their framework to study moderators that could potentially influence how CVC activities contribute to a parent company learning processes.

The authors identified four factors groups that could have a potential impact on organizational learning. The first group are characteristics of the donor firm. The second represents the characteristics of the recipient firm while the third show the nature of the knowledge shared. Finally, the fourth represent inter-organizational dynamics. The third factor, characteristics of knowledge, will not be considered as a moderator in this study as ambiguity is already part of the second sub-question.

Thus, the first group of potential moderators analyzed is the recipient firm characteristics. In a CVC relationship, the recipient firm is the parent company. Easterby-Smith, Lyles et Tsang (2008) propose three moderator factors. The firm absorptive capacity has been identified as having an impact on the ability of the firm to transfer knowledge as explained above (Lane, Koka et Pathak, 2006; Zahra et Hayton, 2008). Also, intra-organizational knowledge transfer capacity has been highlighted by Easterby-Smith, Lyles et Tsang (2008) as an important factor. The ability to diffuse acquired knowledge inside the firm boundaries has an impact on organizational learning. Finally, the motivation to learn could moderate the impact of CVC on organizational learning. It has been recognized as a determinant in the extent of knowledge being transferred (Hamel, 1991).

The second group of potential moderators is the donor firm's characteristics. In a CVC relationship, donors are the CVC programs and the ventures. The CVC units need to acquire knowledge from the ventures and transfer it back to their parent companies. The factors selected here differ from Easterby-Smith, Lyles et Tsang (2008) framework, as they are adapted to a CVC context. For a CVC

unit, prior experience with other entrepreneurial ventures could be the first factor. An experienced team could be better suited in identifying relevant pieces of knowledge to be transferred to their parent company. The donor's motivation to teach is also another important factor according to Easterby-Smith, Lyles et Tsang (2008). In the case of the CVC, an entrepreneurial venture could either feel motivated to provide knowledge to a CVC unit, in the case where it receives resources and access to the parent company (Pahnke, Katila et Eisenhardt, 2015). Or it could try protecting its knowledge from the CVC unit fear of knowledge misappropriation (Katila, Rosenberger et Eisenhardt, 2008).

Finally, the last group of moderators focuses on inter-organizational dynamics. In fact, these dynamics could have an impact on the level of support and resources given to the CVC programs. In this research, three main factors will be analyzed. The first factor is trust. Greater trust between partner facilitates organizational knowledge exchange (Lane, Koka et Pathak, 2006). The second factor is social relations. In their framework Easterby-Smith, Lyles et Tsang (2008) mention that superior tie strength could have an effect in lowering barriers between partners, thus increasing organizational learning opportunities. In addition, CVC ties can increase the amount and variety of knowledge flow available to an investing firm's innovation effort (Wadhwa, Phelps et Kotha, 2016). The third factors are the CVC structure and transfer mechanisms. Structure represents the way the CVC unit is managed. The mechanisms could involve the monitoring activities of the CVC unit on the ventures through observer rights (Keil, Autio et George, 2008), board memberships (Wadhwa et Kotha, 2006), training members of the recipient firm (Easterby-Smith, Lyles et Tsang, 2008) or collaborating in blueprints development (Wadhwa, Phelps et Kotha, 2016).

The following figure depicts the conceptual framework of this research. It was created in accordance with the main arguments presented above and was conceptualized using empirical studies from Simonin (1999), Easterby-Smith, Lyles et Tsang (2008) and Lane, Koka et Pathak (2006). It was particularly relevant to use these studies as a basis for theory building as they analyze in detail organizational learning, as well as antecedents and moderators of inter-organizational learning.

3.3 Conceptual framework model

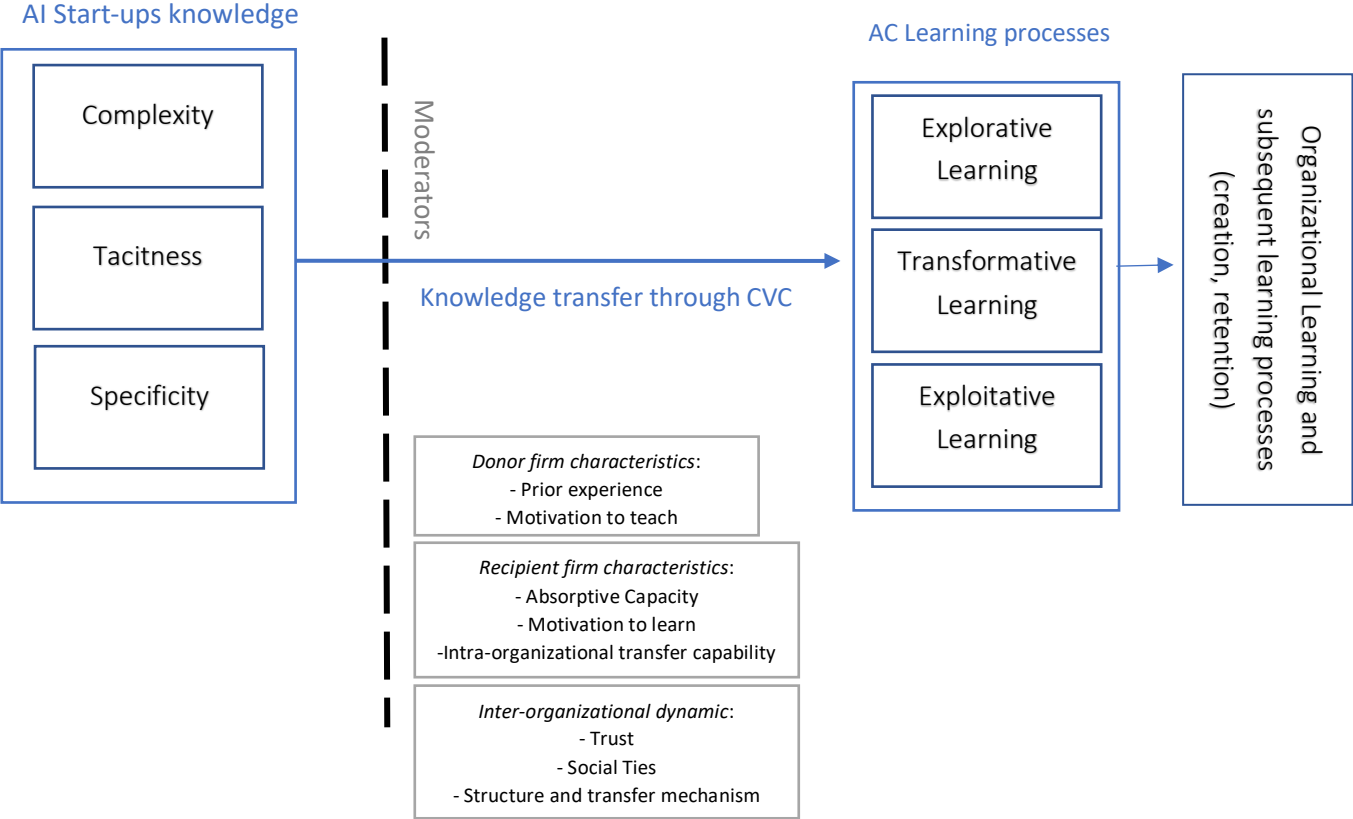


Figure 8 - Conceptual framework model– adapted from Simonin (1999), Easterby-Smith, Lyles et Tsang (2008) and Lane, Koka et Pathak (2006)

Chapter 4 Research Setting

To answer the three research sub-questions, this study investigates Japanese and French AI CVC investments. It is relevant to study this setting, as Japan and France are countries currently developing their AI expertise. French or Japanese companies conducting research or applying AI in their activities are still marginal, despite a surge in public and private AI funding in recent years. AI research today is mainly concentrated in North America with large corporations such as Google and Facebook currently massively investing in these technologies (Scappaticci, 2018). Hence, analyzing Japanese and French firms is a good way to determine whether CVC contributed to Japanese and French companies AI learning activities, in countries with scarce experiences.

4.1 AI Context

AI In Japan

Every five years, Japan announces its new plan for nationwide science and technologies priorities. These priorities are specified by the prime minister's office (CSTI) (MEIRIES, 2018). The 5th plan, launched in April 2016, describes the key concept of the 5.0 society, otherwise designated as "ultra-intelligent" society. Its aim is to respond to the Japanese society's current challenges (including aging population, productivity decrease, competitiveness issues) through a new digital revolution centred around AI, robotics and the internet of things (Scappaticci, 2018).

The Japanese government has already contributed to some major public AI funding and created several thinking committees on the use and impact of AI in society (MEIRIES, 2018). Ultimately, the goal of these thinking committees is to stimulate public-private partnerships in order to create value using AI (MEIRIES, 2018). Three Japanese ministries developed their strategies in line with the 5th plan: the ministry of education, culture, sports, sciences and technology (MEXT), the ministry of economy and industry and the ministry of internal affairs and communication. Hence, the Japanese government is pushing forward its AI agenda. It is highly probable that this research and development effort will help the country in creating expertise in AI, as universities, research centre and companies work in pairs in this attempt (Scappaticci, 2018).

Morikawa (2016) surveyed more than 3,000 Japanese firms to be au fait with the Japanese business world's attitude towards AI. Japanese companies overall have a positive view on AI technologies (Morikawa, 2016). The author reports that around 27,5% of Japanese firms have a positive attitude towards the development and diffusion of AI (3,9% have state that AI will have a significant positive impact while 23,6% only report a positive impact). On the other side of the spectrum, only 1,3% of firms think the development of AI will have a negative impact on future business. However, most firms simply do not have a clear outlook on AI technology and answered that AI will neither have a positive or negative impact (71,3%).

No results could be found on AI adoption or usage in Japanese companies. Yet, it is known that the AI market in Japan is expected to grow to 87 trillion yens by 2030 and that the Japanese government expert an economic return on AI of about 121 trillion yen by 2045 (Garcia, 2019). The transport and manufacturing are the economic sectors that are expected to experience the most impact from AI in Japan (Garcia, 2019). The pioneer companies in Japan are mostly Japan's major companies, such as NEC, Fujitsu and Toyota. In November 2016, those corporations, such as Fujitsu, Toshiba, Hitachi, Panasonic and Sharp, announced their intention to invest in AI research in the years to come, up to 300 billion yens (around 2,7 billion USD) in the next three years (Scappaticci, 2018). Furthermore, Japan is home to several renowned AI start-ups such as Preferred Network, Tier IV, LeapMind and UEI Corp, while most start-ups in AI are concentrated in North America (Scappaticci, 2018). Japanese companies engaged in global markets tend to have a more positive attitude towards AI technologies (Morikawa, 2016).

AI in France

Like Japan, the French government actively pushed its AI agenda in recent years. First, it launched the #FRANCEIA initiative with the objective of connecting the different French AI ecosystem actors (institutions, universities, companies) (Ministère de l'économie et des finances et Atawao Consulting, 2019). The government also launched a national AI strategy in March 2018 structured around six major themes, such as the economy, ecology and employment (Ministère de l'économie et des finances et Atawao Consulting, 2019). In total, the French government secured 1.5 billion euros to

make France a global leader in AI (Garcia, 2019). Such policies are fairly recent. French public policies toward AI development are only blossoming. Apart from state policies, the Ile-de-France region (same level of governance as a Japanese prefecture) is the only other public institution having developed an AI strategy (Ministère de l'économie et des finances et Atawao Consulting, 2019).

Tata Consultancy Services et IDC (2018) performed a large study on 900 French companies regarding their view on AI and their AI usage. Seventeen percent of these companies had more than 5000 employees while 42% only had between 200 and 499. According to this survey, 36% of these companies had a strong maturity when it came to AI use, and were already applying AI solutions. Sixteen percent of companies had AI projects coming within 3 years, while 21% were only thinking about implementing AI solutions. 28% had a low comprehension of AI technologies. These rates of adoption varied depending on the industry sector.

According to the French ministry of the economy, the healthcare, manufacturing, transport, utilities and environmental industries were more likely to be impacted by AI in the near future (Ministère de l'économie et des finances et Atawao Consulting, 2019). Yet, the most AI mature industries to date in France were the commerce, financial services and people and goods industries (Ministère de l'économie et des finances et Atawao Consulting, 2019).

French companies reported different barriers to AI adoption. The main one identified by 49% of companies is its cost (Tata Consultancy Services et IDC, 2018). 31% of respondents also pointed out their lack of technological expertise while 28% highlighted that implementing AI solutions was complex. (Tata Consultancy Services et IDC, 2018). 18% mention their lack of understanding of AI technologies and its potential (Tata Consultancy Services et IDC, 2018). Nevertheless, French companies are increasingly investing in AI as reported by this survey: 71% of companies expect to increase their AI budget. Companies with more than 1000 employees have invested on average 825,000 euros in 2017, while companies with fewer than 1000 employees have invested on average 157,000 euros.

AI is still in its early phase in Japan France, even if both governments are pushing AI initiative. While some companies, among them global corporations, invest in AI, it is relevant to mention that a large

part of companies in both countries simply do not have to date a clear outlook of the technology. It might be possible that for them, AI remains an obscure technology.

4.2 CVC context

CVC in Japan

CVC is quite common in Japan (Riney, 2015). In Japan, investment in start-ups has gradually increased from 2009. The following graph depicts this rise. It shows changes in start-up investments amount by type of investor and by year in Japan. It is expressed in 100 million-yen units (approximately 1,26 million CAD). Ind. Inv refers to individuals’ investments while fin. inst refers to financial institutions’ investments. Corporate investments include all investments performed directly by business corporations. CVC investments are accounted as part of VC investments which include all venture capital-related investments.

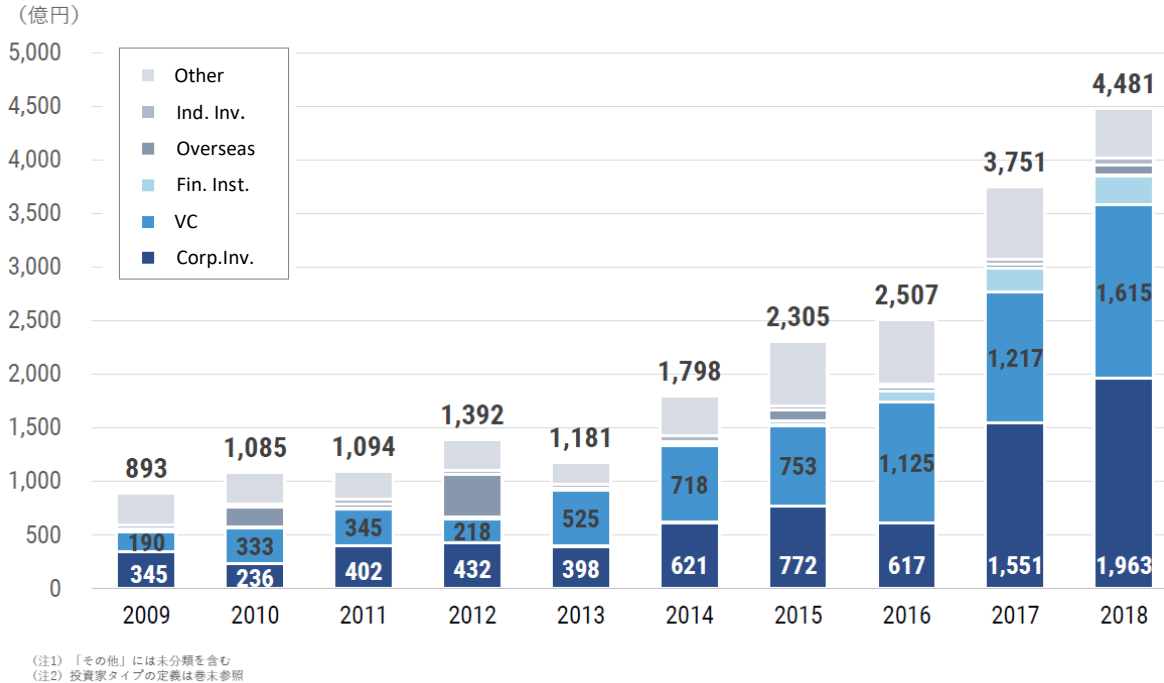


Figure 9 – Investment amount per year by investment type in Japan - (Entrepedia, 2018)

Among the VC amount, CVC constitutes an important part of investments. In 2017, Japanese CVC accounted for 9% of the total amount of Japanese VC investments of 121 billion 700 million yen (1,217 億円) (Entrepedia, 2018). In 2018, this rate increased to 13%, of a total number of VC investments reaching 161 billion 500 million yen (1,615 億円) (Entrepedia, 2018). This evolution can be seen in figure 10 below. In other words, the total investment sum of CVC in Japan in 2018 according to the Entrepedia report was around 20 billion 995 million yen (approximately 294 million CAD). In comparison, in 2018 27% of all Japanese VC investments were performed by VC firms, 33% by financial institutions and 11% were made from overseas VC (Entrepedia, 2018).

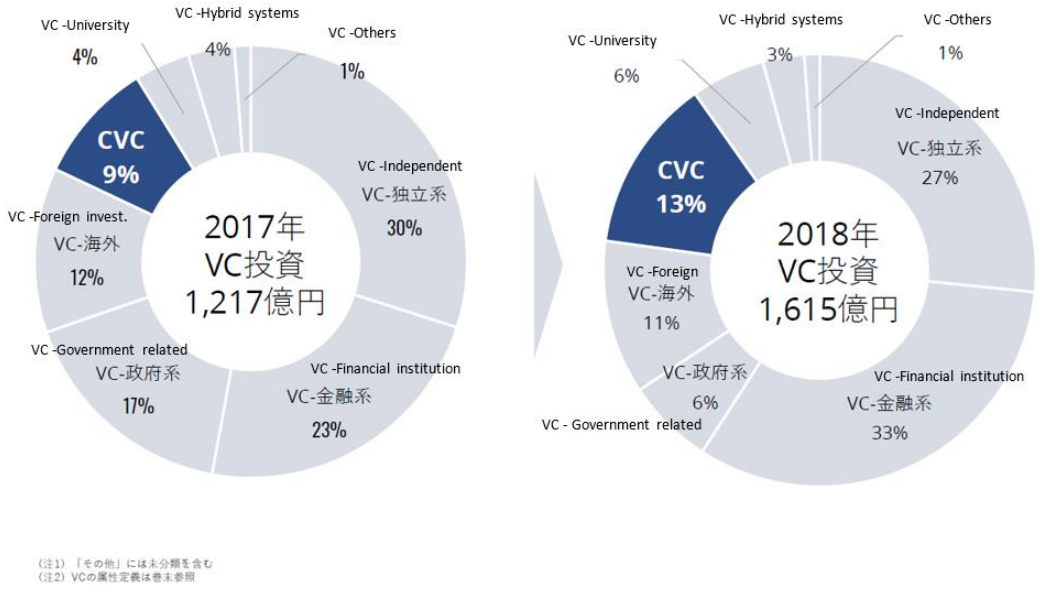


Figure 10 – part of CVC int the total VC amount by VC type in Japan (Entrepedia, 2018)

While CVC in Japan were traditionally focused on telecommunications and manufacturing in the past, there are now new investments being performed in industries such as services and transportation (Suzuki, 2019). This shows the recent momentum surrounding CVC in Japan. To further highlight this increased interest in CVC, Entrepedia (2018) report the creation of 87 CVC units since 2009, 16 of whom were created in 2018 and 13 in 2017 (compared to 3 in 2009 and 3 in 2010).

CVC in France

Compared to a rather large CVC activity in Japan, there were only 38 active CVC units in France in 2018 (Deloitte et Orange Digital Ventures, 2019). However, CVC is an investment strategy that is increasing in the country. The number of investments performed by French CVC has doubled between 2016 and 2018, from 3.5 investments realized per year per CVC to 7 (Deloitte et Orange Digital Ventures, 2019). According to the Deloitte et Orange Digital Ventures (2019) study, half of the CVC realized more than 4,5 investments in 2018 with one CVC unit having realized 22 investments deals.

The average investment in 2018 reached 6,2 million euros, nearly twice the amount of the 2016 average investment amount (Deloitte et Orange Digital Ventures, 2019). 71% of the CVC reported wanting to increase their investment value in 2019. 21% of CVC reported following a financial objective, while 79% had an open innovation investment objective. French CVC favour more mature investment with series B investment representing 67% of total investments (Deloitte et Orange Digital Ventures, 2019). Finally, according to the survey, focuses of investments were in 2018 the transportation, clean tech energy and electronics industries.

Chapter 5 Methodology

5.1 Research philosophy

This research aims to understand how CVC activities contribute to the AI learning processes of its parent company. As such it tends to follow an analysis approach, to gain deep insights regarding a specific situation (Saunders, Lewis et Thornhill, 2012: 171-172).

To get a deep understanding of this research's subject it is necessary to analyze it from "inside", by gathering data regarding individuals' experience. In fact, organizational learning through CVC would first be experienced by actors of such organizational relationship. Taking an interpretivism stance on this research would recognize the importance of human factors in the concepts being studied. Interpretivism sees reality as "a social product that cannot be understood independently of social actors" (Hasan, Subhani et Osman, 2011).

However, one of the main criticisms regarding using an interpretivism stance remains its emphasis on actions and human agency alone, as it is a phenomenological approach (Gioia et Pitre, 1990). This paradigm would not properly value the role played by processes, structures and mechanisms in inter-organizational learning, and would therefore not reflect the objective reality of firms. On the other hand, adopting a functionalist paradigm would perhaps not be the most relevant strategy for this research. Organizational learning would occur through relationships dynamics that may not necessarily be objective phenomenon.

A solution is to adopt a multiparadigm approach by bridging the interpretivist and functionalist paradigms (Gioia et Pitre, 1990). For the authors this "transition zone", called "structurationism" focuses on the dynamics between human actions (in terms of humans "structuring activities") and established firms' structures (organizational design, rules, etc.). Here, structures are defined as "the rules and resources people use in interaction" (Riley, 1983). For the author, structures are both the medium (rules, resources) and outcomes of human interaction in organizations. For Gioia et Pitre (1990) structurationism is a paradigm that can link the subjective view of social interaction (structuring activities) with the objective reality of structures (organizational rules and processes). For the authors structuring activities and structures need to be considered on an equal level,

highlighting the role of social interaction in creating new organizational structures and influencing “subsequent structuring processes”. Said otherwise, people create and recreate structure, forming patterns of their future interactions (Riley, 1983).

This research’s philosophy is based on structurationism. Reality is created by the interaction of social actors in a structured environment. Structurationism links both subjective and objective view of the firm.

5.2 Research Design

The purpose of this research is to understand. This paper does not aim to test and verify the effects of CVC on an AI learning effort, nor the impact of ambiguity on this organizational learning effort. To do so would require an encompassing sampling of CVC units involved in AI activities. Rather, it seeks to grasp the reality of actors, units and firms participating in CVC activities.

A qualitative case study approach can provide answers to such “how” questions (Saunders, Lewis et Thornhill, 2012: 179). This kind of qualitative research allows one to gain deep insights into a situation context and processes (Cooper et Schindler, 2011: 160-183; Eisenhardt et Graebner, 2007; Gerring, 2007: 36). Thus, a case study approach could generate answers on how CVC contribute to the AI learning effort of a firm.

Eisenhardt et Graebner (2007) highlight that using a multiple-case study mitigates the risk of the research being non-representative. One can verify whether a finding is replicated across several cases by establishing comparisons (Saunders, Lewis et Thornhill, 2012: 180; Yin, 1994: 45). This replication logic is central in building theory from case studies (Eisenhardt et Graebner, 2007).

5.2.1 Case selection

The population analyzed in this research is Japanese and French companies engaged in AI investments through CVC units. However, rather than studying parent companies themselves, this research focuses on studying CVC units acting as intermediaries in the knowledge relationships between entrepreneurial ventures and parent companies. Hence, this research uses embedded cases. Embedded cases focus on considering subunits within organizations, for instance business

departments, or in this research case CVC units as pictured in figure 11 below (Saunders, Lewis et Thornhill, 2012: 180).

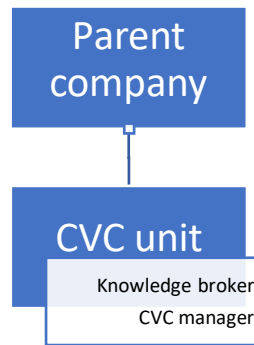


Figure 11 - Unit of analysis

To limit the number of cases, two factors of exclusion have been chosen. The first criteria of exclusion deals with the parent company size. Dushnitsky (2006: 387-431) points out that smaller firms usually tend to lack adequate resources to enter strategic CVC activities. In addition, Keil, Autio et George (2008) point out that external sources tend to be more readily available for larger firms. To ensure representativeness, only large firms will be considered when selecting cases. According to the Japanese company's act of 2005, a "Large company" in Japan is any stock company satisfying the following requirement (free translation) (法務省 Ministry of Justice, 2005):

- The amount of stated capital in the most recent business year balance sheet is 500,000,000 yen or more (art. 1, (vi), a); or
- The total sum of numbers in the liabilities section of the balance sheet as the end of the most recent business year is 20,000,000,000 yen or more (art. 1, (vi), b);

To simplify cases selection, the same definition has been used to select French companies.

The second factor of exclusion is related to the CVC unit's investments. For obvious reasons, the CVC units must have completed investments in AI-related ventures. These investments must have been undertaken for a minimum length of six months, to guarantee there was enough time for

knowledge transfer and organizational learning to happen. Third, the investments must have been made after 2010, around the time surge in AI investments has been observed.

Heterogenous purposive sampling

One flaw rising from the use of qualitative data is the difficulty generalizing the research's results to a large population (Cooper et Schindler, 2011: 160-183). Case studies produce said flaws, as they only provide theoretical propositions (Eisenhardt et Graebner, 2007). A solution to deal with this issue is to properly select cases, to make sure they are relevant to "the breadth of the issue" (Cooper et Schindler, 2011: 160-183).

Selecting cases through heterogeneous purposive sampling may ensure internal and external validity. This method provides maximum variation in a set of data by choosing cases with sufficiently diverse characteristics to represent the full variation of the population (Saunders, Lewis et Thornhill, 2012: 287). However, it is crucial to note it might not mirror precisely "the distribution of that variation in the population" (Gerring, 2007: 89). Yet, any variation rising from heterogeneous sampling enhances the selected cases representativeness (Gerring, 2007: 86). To gain a representative sample of the French and Japanese companies engaged in AI CVC investments, and to guarantee maximum variation, we used three characteristics. Two were previously identified by Basu, Phelps et Kotha (2016) and Chesbrough (2002). Those characteristics are the parent company industry sector and CVC strategic objectives. In addition, we considered the CVC units' investment focus as a third criterion for representativeness.

The first criteria to select cases was made according to the parent company industry sector. According to Basu, Phelps et Kotha (2011), companies belonging to industries "with rapid technological change, high competitive intensity" or companies having "strong technological and marketing resources" tend to engage more in CVC activities. In this context, it seems reasonable to think certain industries would be more inclined than others to invest in AI-related start-ups through CVC. In France, industries facing a high AI impact in the future would be the manufacturing (including automotive and energy), transportation, information technologies and communication ("ICT") and healthcare industries (Ministère de l'économie et des finances et Atawao Consulting, 2019). In Japan, AI is a technology that could attract industries such as ICT , manufacturing (including automotive),

transportation and finance (Garcia, 2019; Tsutamoto et Yamakawa, 2017). It is therefore expected that companies operating in the manufacturing, ICT, transportation, finance and healthcare industries would be more inclined than others to sustain AI CVC activities.

In Japan, the 総務省 - Ministry of Internal Affairs and Communications (2008) currently lists 20 different business sectors. Table 6 shown below highlights this classification. The same classification is used to select French companies for simplicity reasons.

Table 6 - Japan Standard Industrial Classification, 総務省 - Ministry of Internal Affairs and Communications (2008) – Free translation

#	Classification Item Name	Main content
A	Agriculture, Forestry	Agriculture, farming, forestry service industry
B	Fishery	Sea surface and inland water fishery, aquaculture
C	Mining, Quarrying, gravel sampling	Metal, Coal, Oil, Gas, Quarrying mineral mining industries
D	Construction industry	Civil engineering, construction-related works
E	Manufacturing industry	Food-transformation, Textile, Wood-transformation, Furnitures, Chemical, Petroleum & Plastics, Metal transformation, Industrial machinery, Electronic components, IT, Information communication machinery & Equipment manufacturing industry, car
F	Electricity, gas, heat supply, water supply industry	Electricity, Gas, Heat & Water supply
G	Information and Communication industry	Communication, Broadcasting, Information Service, services incidental to Internet
H	Transportation Industry, Postal Service	Railway, Air & Road transportation, Water transport, Post
I	Wholesale and Retail	Wholesale & Retail industries
J	Finance industry, Insurance industry	Banking, Cooperative, Trading, Insurance
K	Real estate industry, Goods rental business	Real estate, Item rental industries
L	Academic research, specialized / Technical service	Academic institutions, Law office, Accountant offices, Advertising industries
M	Accommodation industry, food service business	Hotel, Restaurant, Food-delivery services
N	Lifestyle related services, entertainment industry	Beauty industries, Travel, Ceremonies, Entertainment, Sports
O	Education, learning support industry	School education, learning support industry
P	Medical care	Medical industry, Health hygiene, Social insurance
Q	Composite service business	Post office, Cooperative association
R	Service industry (not classified elsewhere)	Waste disposal, Automobile maintenance, Repair work, Religion
S	Public affairs (excluding those classified elsewhere)	State public affaires, local public affairs
T	Unclassifiable industry	other

The second criteria deal with CVC objectives. The CVC objectives should reflect either financial or strategic objectives (learning, leveraging option building) as depicted by Maula (2007) in table 5 of the literature review.

The third criteria is to confirm whether the investments performed by the CVC units are representative of worldwide CVC investments. Dushnitsky (2011) specifies that software and IT-related sectors (G & E) make up for the majority of CVC investments worldwide, followed respectively by biotechnology ventures (P), semiconductor sector (E), medical devices and health care services sectors (P) and finally media and entertainment (N). In 2018 in France, the main CVC investments focused on software and IT-related sectors (G & E) as well as in the transportation and mobility sector (H & G) (Deloitte et Orange Digital Ventures, 2019). No data was available for Japan.

Table 7 - Cases selection criteria

Units of analysis - Criteria of exclusion		
The parent company is not considered a "large" company under Japanese or French law		CVC investments are not in AI – AI investments were made in the last six months or before 2010
Heterogeneous purposive sampling – Criteria ensuring maximum variation		
Parent company industry	CVC units objectives	CVC units investment focus

5.3 Data collection

The data collection process took place in three stages. First, cases suitable for the research were identified and mapped. In the following two stages, primary and secondary sources were collected. In using two types of data source, we ensure proper data triangulation (Saunders, Lewis et Thornhill, 2012: 179). Using different data source allows for complementarity, enhancing or confirming eventual findings (Saunders, Lewis et Thornhill, 2012: 169). Primary data comes from semi-structured interviews. On the other hand, data was also retrieved from secondary sources such as companies' documentation or reports.

Selecting cases

To select cases, this essay mapped the number of firms that invested in AI through CVC in Japan and France. Scholars, such as Dushnitsky et Lenox (2005a) have relied on CVC databases, such as the VentureXpert database, to list a wide and scientifically acceptable number of CVC investments. This study used this kind of database to reach the largest number of Japanese and French companies. The following list provides the name of databases that were used for this research:

- Thomson's VentureXpert (otherwise known as ThomsonOne Private Equity) – University access
- Dow Jones VentureSource (otherwise known as VentureOne) – Internet access
- Crunchbase (Transaction-level detail) – Internet access
- Entrepedia (Japanese venture equity transactions) – University access

In addition, sources of information such as economic newspapers (Nikkei, the Japan times, Les Echos) were used to identify a larger pool of potential respondents.

The first step was then to collect information from these databases and compile them in a general file. This effort was performed throughout the months of July and August 2019. Criteria of exclusion were applied to eliminate irrelevant candidates.

Using Venture Xpert, Dow Jones Ventures and Entrepedia databases, 1228 CVC investments transactions were identified as having been performed by Japanese firms. Of those, 452 transactions occurred in the last 10 years, performed by 92 different CVC units all belonging to large corporations. Using Entrepedia and CrunchBase databases, as well as various newspapers sources (such as Nihon Keizai Shimbun, Asahi Shimbun, Bloomberg), investments activities of those 92 units were analyzed to see whether they invested in AI-related ventures during the past decade. The number of CVC units having undertaken AI-related investments from 2010 in Japan added up to 43 units. Those units belonged to 40 different parent companies. Parent companies of these units belonged mainly to the ICT, finance and manufacturing business sectors (as shown in figure 12 below), as predicted by Tsutamoto et Yamakawa (2017).

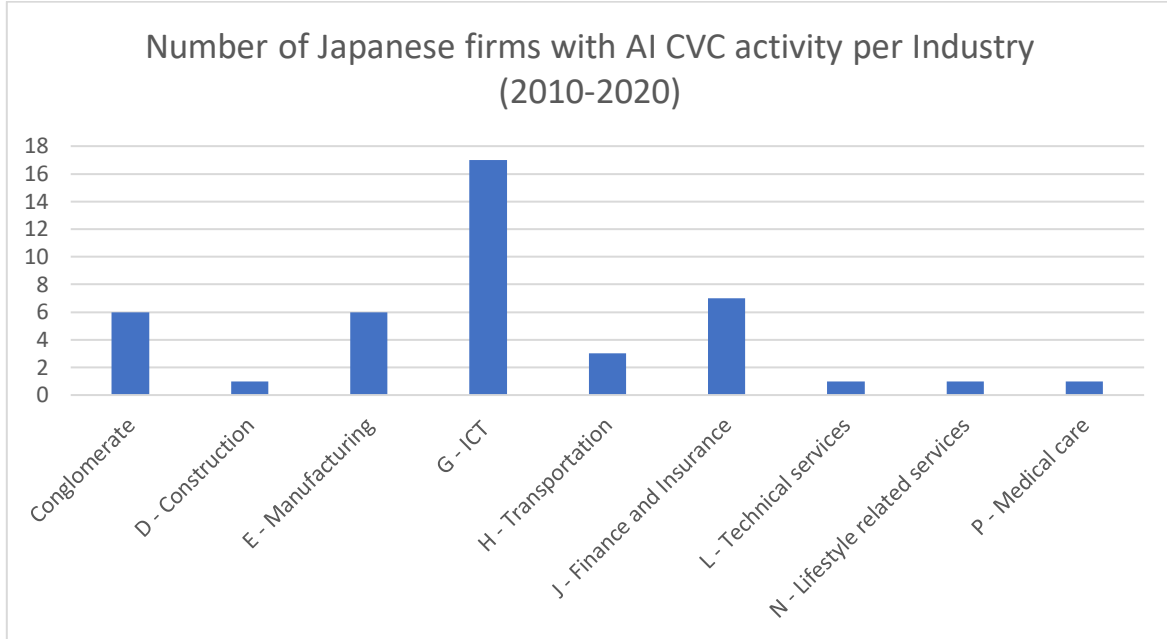


Figure 12 - Business sectors of Japanese firms with AI CVC activity

In France, where the CVC activity is less intense than Japan, only 38 CVC units were active in 2018 according to Deloitte et Orange Digital Ventures (2019). These 38 CVC units all belonged to large companies (following the 法務省 Ministry of Justice (2005) of large company). Using the Crunchbase database and economic newspapers (les Echos, la Tribune, etc.) investment activities of these units were reviewed to further eliminate irrelevant units. In France, out the 38 CVC units identified, 12 were identified as having undertaken AI-related investments. They belonged to 11 different companies. Those 11 companies belonged to the manufacturing, ICT, finance and transportation industries as shown in figure 13 below.

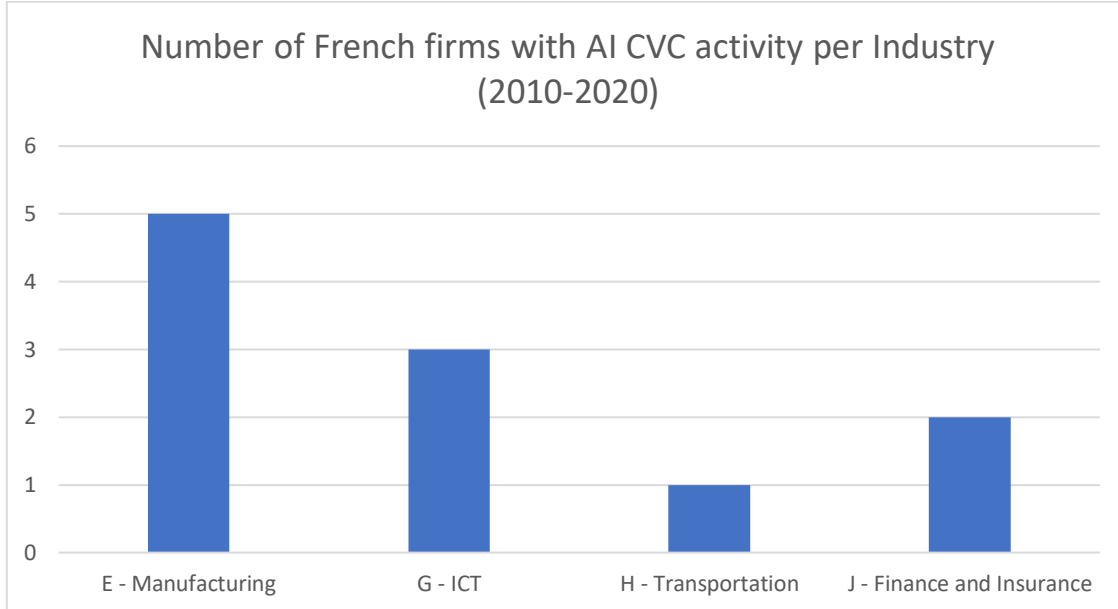


Figure 13 - Business sectors of French firms with AI CVC activity

Primary Data: Interviews

Semi-structured interviews were performed in this research. Using an in-depth interview format was deemed appropriate as a series of complex questions had to be answered which require open-ended format (Saunders, Lewis et Thornhill, 2012: 379). To obtain useful information from the interviews, informants must have had a key role in their respective units. Specifically, they needed to be involved in AI learning activities or AI investments. In CVC units, the relevant person was identified as the CVC manager or CVC principal.

Participants were first contacted by e-mail. Those e-mails were not sent to the parent company but were sent directly to the CVC unit. This exercise was performed from mid-September 2019 to mid-December 2019.

Whenever possible, academic or business contacts were used to get in contact with participants. Otherwise, potential contact information was gathered from the internet, or by communicating with the CVC unit or parent companies' reception via e-mail. If an e-mail remained unanswered for two

weeks, a follow-up message was sent. In France, LinkedIn was used as a tool in trying to get in contact with potential participants. E-mails were either sent in English, French or Japanese. The e-mail model is shown in appendix 2.

In Japan, 43 e-mails were sent to CVCs. Out of this number, 36 remained unanswered, three people refused the interview, five accepted it. Two participants came from the same CVC unit. Out of the five people who accepted the interview, two accepted it following a recommendation. Four interviews were performed in person, while the other was made on video call. All were made in English.

Japanese participants were asked at the end of each interview whether they could provide the contact information of other relevant people at their parent company or CVC unit that would be willing to participate in this research. Unfortunately, all participants refused to provide such information.

In France, 12 numbers of requests for interviews were sent to CVCs. Nine remain unanswered, three units accepted the interviews. Two members from the same CVC unit participated in one of the interviews. All interviews were performed using video conference, in French. Of the three interviews, one was the result of a recommendation. Like Japanese companies, it was not possible to secure additional interviews with other relevant people of the same CVC units.

To contrast results obtained from the CVC units' interviews, three additional interviews were also organized with actors of different open innovation schemes: An R&D program, an accelerator, and a VC firm. Gaining their perspectives was thought to help contrast how CVC contributed to AI learning compared to other structures. In Japan, e-mails were sent to one acceleration program manager and a research program manager. Those e-mails came with recommendation. Both managers accepted the interview. One interview was performed in person, while the other was made using video call. The interviews were performed in English. In France, one former AI entrepreneur, now CEO of a VC fund, was also contacted and accepted the interview, which was performed in French.

In total, 11 people agreed to the interviews. A consent form was sent to all participants that agreed to be interviewed in compliance with the ethics bureau of HEC. All participants have agreed to have their interviews recorded for research purposes.

The interviews detail is shown in table 8 and table 9. For anonymity and confidentiality purposes, the companies' names have been replaced with city names randomly. The companies' head offices are not situated in any of those cities.

Table 8 - Case study details

Company	Identification	Home country	Unit established in	Activity Sector	Number of interviews	Structure
Aomori	A	Japan	Japan	K	2	CVC
Kagoshima	KA	Japan	Japan	G	1	CVC
Saitama	SA	Japan	United States	G	1	CVC
Takayama	TA	France	Japan	G	1	Acceleration program
Nagano	NA	Japan	Japan	E	1	CVC
Hakodate	HA	Japan	United States	E	1	Research program
Marseille	MA	France	France	G	1	CVC / R&D department
Yainville	YA	France	United Kingdom	E	1	CVC
Rambouillet	RA	France	France	J	1 (two people)	CVC
Waller	WA	France	France	J	1	VC / entrepreneur

Table 9 - Interviews detail

Company	Identification number	Position	Interview length
Aomori	T-1-1	Executive Manager	55mn
Aomori	T-1-2	Principal	23mn
Kagoshima	T-2-1	Managing Director	57mn
Saitama	T-3-1	Senior Vice President	1h00

Takayama	T-4-1	Partnership Manager	57mn
Nagano	T-5-1	CEO, CVC	59mn
Hakodate	T-6-1	Director, Business Development	1h07mn
Marseille	P-1-1	Innovation Director	1h06mn
Yainville	P-2-1	Analyst	39mn
Rambouillet	P-3-1	Managing Partner & Global head of business development (2 people)	51mn
Wallers	P-4-1	CEO	47mn

The interviews were conducted with the help of an interview guide (available in appendix 3) to ensure a reliable primary data collection. The latter supports the semi-structure interviews process. It provides a balance by setting limits to the interviews, warranting that all data is linked to the subject, and by guaranteeing that each interviewee is free to express its views (Saunders, Lewis et Thornhill, 2012). The interview guide was written based on the research sub-questions and on relevant prior research. If the interviewee came from another structure than a CVC, this research guide was modified accordingly.

The interview guide was separated in four parts. Following Keil, Autio et George (2008), the first part of the interview guide is used to gather background information on the interviewee. This part helps in getting additional information on the interviewed firm's industry reality, corporate and business strategy regarding AI or CVC in general, the role and responsibilities of the interviewee in the firm. The second part, built on Keil, Autio et George (2008) and Zheng Zhao, Anand et Mitchell (2016), seeks to uncover the sequence of knowledge transferring activities between the actors in the CVC relationship. The third part focuses on understanding the outcomes of AI knowledge transfer process on the parent company learning. It provides information regarding the units' goal of investing in AI. The fourth part was centred around moderators, to identify both enablers and inhibitors in CVC relationships. Once again, this guide was modified to fit interviews performed with actors that were not part of a CVC program.

Open-ended questions enabled interviewees to reply freely and answer as widely as they chose to (Eisenhardt et Graebner, 2007). Some questions were derived from tested qualitative works, such as Andrew C. Inkpen et Crossan (1995). Should some key elements be mentioned and not developed by the interviewee, or should the interviewee's answers be considered too brief, additional questions or probes addressed that gap (Patton, 2002: 372). This was made to gain more accurate pieces of information, as prescribed by Eisenhardt et Graebner (2007). The questions were designed to ensure clarity (Patton, 2002: 361). In addition, since the interviews were cross-cultural some of the research terms were carefully reviewed to ensure both interviewer and interviewee shared similar meaning and understanding of the research key concepts (Patton, 2002: 391-392). When the questions were not understood by the interviewee, they would be rephrased.

The steps taken, described above, were thought to provide consistent and reliable data, thus limiting bias (Eisenhardt et Graebner, 2007).

Secondary data

Secondary data consists in data that have been collected previously for another purpose than the research objective (Saunders, Lewis et Thornhill, 2012: 304). The authors highlight several advantages and disadvantages to using secondary data. This type of data is generally unobtrusive and less expensive than primary data. Using secondary data also provides comparative and contextual data that could support the research (Saunders, Lewis et Thornhill, 2012: 304). However, secondary data may not match the research needs and may be difficult to access. Quality of data can also be questioned, as researchers have no control over such data (Saunders, Lewis et Thornhill, 2012: 304).

Using secondary data helped this research. First, it enabled additional understanding of the phenomenon being studied. Primary data was unfortunately limited to 11 interviews. Besides, some pieces of information would have been difficult to gather through interviews, such as CVC transactions information, whereas it could be found easily using secondary data. Using secondary data also increased this research reliability, specifically through triangulation.

The first type of secondary data used came from CVC databases. These databases were used to study AI investments performed by the CVC unit (sector of activity, maturity, etc.), the dates of investment as well as the amount invested by the firm.

The second type of documents were companies press release and other internal documents such as financial reports. Press release informed why CVC units invested in a given venture. They could reveal the investment strategy of a CVC unit and its parent company, especially regarding AI. They gave information on the target for explorative learning. Financial statements also contained valuable information as they often comprise message to investors. In such messages, the top management of a company often introduces the state of research or innovation at the firm. Such information can also be available on the parent company website, and occasionally on the CVC website.

The third type of document consisted in press articles from specialized or general media. Such documents informed on AI innovation produced by companies, for example in the form of new product release. It also informed on the difficulties encountered by companies when it came to AI R&D.

5.4 Analysis process

Analysis method

This paper followed the five steps analysis cycle proposed by Yin (2011: 177). This cycle consists in compiling, disassembling, reassembling, interpreting the data and finally concluding on the results. This part focuses on explaining the three first steps.

The first step consisted in compiling, or organizing, the data. All interviews were transcribed. They were double-checked to ensure accuracy. Each file was saved separately and assigned an identification number to preserve anonymity. Those files were grouped in a folder dedicated to each case (Saunders, Lewis et Thornhill, 2012: 551). A copy of each file was then saved in a secure private cloud service. In the same way, secondary data such as electronics documents were organized for

analysis, classified using an identification number, and checked for accuracy (Saunders, Lewis et Thornhill, 2012: 513). To ensure reliability, the accuracy of data from primary and secondary sources was checked twice as suggested by Yin (2011: 177).

Analysis strategy

This paper chose an analysis strategy prior to disassembling data. An induction strategy was thought to be the best suited approach to understand a phenomenon that had not been treated before in the CVC and organizational learning literature (Saunders, Lewis et Thornhill, 2012).

Relying on previous theoretical propositions from the literature helped direct the data analysis (Saunders, Lewis et Thornhill, 2012: 549; Yin, 1994). For the authors, linking one's research to an existing body of knowledge provides an initial analytical framework. It was useful in identifying the main variables and components of this research. Therefore, the analysis merges a deductive thinking and an inductive approach in analyzing the data.

The second and third step of the analysis consisted in disassembling the data and reassembling it. This effort was performed by assigning categories and codes to parts of the data (Yin, 2011: 178). Since the analysis links an initial analytical framework to an inductive approach, categories and codes were mostly derived from the literature. Nevertheless, they were also derived from terms used by interviewee as well as emerging terms (Saunders, Lewis et Thornhill, 2012: 557). The first level analysis was usually performed with codes derived from the literature while the second analysis was made following readjustment to emerging codes (Saunders, Lewis et Thornhill, 2012: 557). Categories and code were readjusted along the data analysis to ensure convergence in data (Patton, 2002: 465). As suggested by the author, categories and codes were created by looking for recurring regularities in the data. This step ensure, in turn, internal homogeneity and external heterogeneity (Patton, 2002: 465). They were followed to ensure other scholars could reproduce similar categories or codes.

Methodology quality

Multiple steps have been taken to ensure this research reliability and validity.

First, efforts were made to assure the research trustworthiness and credibility. The data collection techniques and analytic procedures used in this essay should produce consistent findings if they had to be repeated or replicated by a different researcher (Saunders, Lewis et Thornhill, 2012). As prescribed by (Yin, 2011: 19), the research procedures are transparent. The methodology has been carefully detailed to ensure anyone understands the different steps taken in this research.

To further ensure reliability, a case study database has been used. All documents pertaining to each case study were gathered on unique folders. Files containing the transcribed data from the interviews were separated from the codified version of the interviews, for the transcribed data to be checked by an external party if required (Patton, 2002; Yin, 1994).

In using two types of data source, we ensure proper data triangulation (Saunders, Lewis et Thornhill, 2012: 179). Performing cross-case analysis allowed to confirm or infirm some findings. Secondary data was then used to corroborate primary data. Using those different data sources were used to ensure complementarity, enhancing or confirming eventual findings (Saunders, Lewis et Thornhill, 2012: 169). Whenever possible, several interviews were conducted for each case. However, most of the primary data gathered was the result of a single interview per case, which could represent a limit.

Efforts were also taken to ensure the research's validity.

The conceptual framework and its different units of measures were based on existing studies of Simonin (1999), Easterby-Smith, Lyles et Tsang (2008) and Lane, Koka et Pathak (2006). The interview guide used in this research was also developed using proven studies. All those steps were taken to ensure construct validity.

Selecting cases through heterogeneous purposive sampling was thought to ensure the internal and external validity of this study. One limit may be that the population of research participants, while diverse, might not mirror precisely "the distribution of [the] variation in the population" (Gerring, 2007: 89). External validity was further guaranteed using a multiple-case study, which following a

replication logic, mitigated the risk of the research being non-representative (Eisenhardt et Graebner, 2007; Saunders, Lewis et Thornhill, 2012: 180; Yin, 1994: 45).

As mentioned previously, one flaw rising from the use of qualitative data is the difficulty generalizing the research's results to a large population (Cooper et Schindler, 2011: 160-183). However, the cases selected for this study were thought to be relevant to "the breadth of the issue" analyzed (Cooper et Schindler, 2011: 160-183). Details regarding the research context were provided for researchers to identify whether this research is transferable to their situation.

The goal of the analysis cycle was to guarantee "substantial significance" to this research findings (Patton, 2002: 467). In other words, it was performed to make sure the evidence supported the findings, and that the findings were consistent and useful (Patton, 2002: 467).

Chapter 6 Data analysis

6.1 Data presentation

The first part of this section will focus on presenting the various units that participated in this research. It is thought relevant to understand the objectives and motives of each unit, their existing AI expertise and their rationale for investing in or working with AI, before analyzing how these activities contributed to their parent companies AI learning processes.

Ten organizations participated in this research. Seven of these organizations were CVC units. The remaining 3 organizations were respectively an accelerator program, a research program and a private VC fund. The head of the VC fund was also a former AI entrepreneur. Including the accelerator and research program enabled this research to compare how the CVC structure differed from other open innovation structure in contributing to AI learning processes. Including the VC fund allowed to contrast how two venture structures deal with learning when investing in AI start-ups. In addition, analyzing the insights of a former AI entrepreneur, now VC fund head, allowed to gather details regarding the perspective of an AI start-up working with a large company.

Apart from the VC fund, all units belonged to large companies. All CVC units had been involved in AI investments activities for at least 6 months, and their AI investments took place after 2010. The accelerator and research fund had also been interacting with AI start-ups for more than 6 months, from 2010.

The units interviewed were on average established seven years ago. The youngest unit was established four years ago while the eldest had 14 years of experience. The following graph shows the repartition of units by their year of establishment.

Table 10 - Distribution of units interviewed by years of establishment

Years of establishment	Number of units
0 to 4	2
5 to 8	4
9 to 12	2
13 and up	2

To ensure the CVC units selected were representative, this paper used 3 different criteria's: the parent companies' business sector, the CVC unit objectives and the investments sectors.

The following graph shows the units' parent companies repartition by industries, classified under the Japanese standard industrial classification system (the VC unit was omitted). Sectors supposedly investing more than others in AI should respectively be the ICT (G), manufacturing sector (E), transportation (H), finance (J) and healthcare (P) sectors (Ministère de l'économie et des finances et Atawao Consulting, 2019; Tsutamoto et Yamakawa, 2017).

Using the first criteria, the CVC units selected were representative to a certain extent. Three CVC units belong to the ICT industry (G), two from the manufacturing industry (E) and one from the finance industry (J). The last one belongs to the real estate industry (K). No CVC units belonged to the healthcare sector.

The accelerator and research program were also analyzed. The parent company of the first unit belongs to the ICT industry (G) while the second belongs to the manufacturing industry (E). The VC interviewed, not included in the following graph as it is its own private company, belongs to the category J.

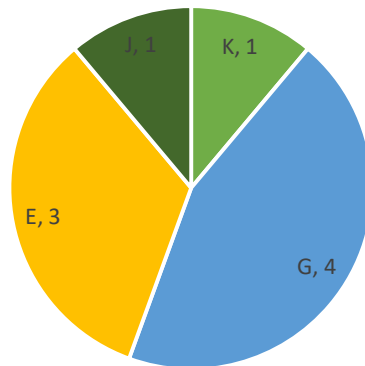


Figure 14 – Units’ parent companies industries

To be representative, CVC units also had to operate following a financial or strategic objective. The CVC selected managed their units through various objectives that are thought to be representative. The objectives have been categorized using Maula (2007)’s framework of CVC objectives. One strategic objective, business synergies, has been added to this framework as it was mentioned by some CVC units throughout the data collection process.

The acceleration program, the research program and the VC fund have been excluded from this section, as the criteria does not apply to their structure.

Table 11 - Units objectives reported by CVC participants

Objectives	Example	Units	Verbatim record	% of CVC units
Financial Objective				
Financial Gains	Financial returns	Kagoshima, Nagano, Yainville, Rambouillet	“We have to aim for two objectives. One is business development and the other is financial results” KA	57,1%
			“We are not neglecting the financial returns, but I emphasize the strategic returns” NA	
			“We have a pure VC objective; our investment structure aims at optimising its financial return [...] though we will not invest if it does not have synergies with [our company]” YA	
			“Our main objective is financial gain” RA	
Strategic objective				

Business Synergies	Business development	Kagoshima, Nagano, Yainville	<p>“Our mission is to create the future core of [our company] [...] [we want to] develop a win-win situation together” NA</p> <p>“our goal is to help [our company] speed up its innovation cycle [...] by working with the best start-up” YA</p>	42,9%
Market-level learning	Radar-like identification of, monitoring of, and exposure to new technologies, markets and business models	Aomori, Saitama, Nagano, Marseille, Rambouillet, Yainville	<p>“I always define ourselves as the explorer of innovation of [our group]” A</p> <p>“we should know what technologies should be implemented [...] It is kind of understanding the market, understanding the business [...] [We focus] on new technologies for [our] group for future business priorities” SA</p> <p>“We have a very large vision of our subject, we are not dedicated to a strategic objective in terms of [market] screening” RA</p> <p>“It allows you to be in an explorative mode, to take a step back and think about subjects the teams do not have time to explore” YA</p>	85,7%
Venture-specific learning	External R&D, improving manufacturing process	Aomori, Saitama, Marseille	<p>“We should do the investment in a R&D context [...] we invest in minor portion into the original or main idea for understanding the market research development” SA</p> <p>“I work on subjects that are not addressed by the different departments, on subjects they can’t address due to a lack of expertise or time” MA</p>	42,9%
Indirect learning	Change corporate culture, train junior management, learn about venture capital			0%
Option building	Options to acquire companies, option to enter new markets	Nagano	“Through this investment, we can see how the market accept their technology [...] it is really a good way to explore new markets” NA	14,3%
Leveraging	Leveraging own technologies and platforms, leveraging own complementary resources			0%

Finally, the third criterion for representativeness was to confirm whether the general investments performed by the selected CVCs were typical investments for CVC units. Most CVC investments worldwide go to the ICT sector (G), followed by the manufacturing sector (E), the healthcare sector (P), the media and entertainment sector (N) and the transportation sector (H) (Deloitte et Orange Digital Ventures, 2019; Dushnitsky, 2011).

The seven CVC units interviewed all had more than 10 active investments. The majority had fewer than 30 active investments.

Table 12 - Distribution of CVC units interviewed by number of active investments

Number of active investments	Number of CVC units
10 to 30	4
30 to 50	1
50 to 70	1
70 and up	1

Taken together, the seven CVC programs had 254 ongoing investments. Of those investments, 64 were investments made in AI-related start-ups, or 25% of the total sum. In all the CVC units, their respective proportion of AI investments to the total number of their investments was approximately equal to 25% as well. For five of the seven CVC units, AI was identified clearly by respondents as a priority investment sector.

The CVC units selected are representative of CVC units in general, when looking at the third criteria. Of the 254 investments performed by the seven CVC units, 53% went to the ICT sector (G), 13% to the manufacturing sector (E), 8% respectively to the healthcare (P) and finance (J) sectors, and 5% to the media and entertainment sector (N). The remaining 13% went to 7 other sectors. Figure 15 below highlights this situation.

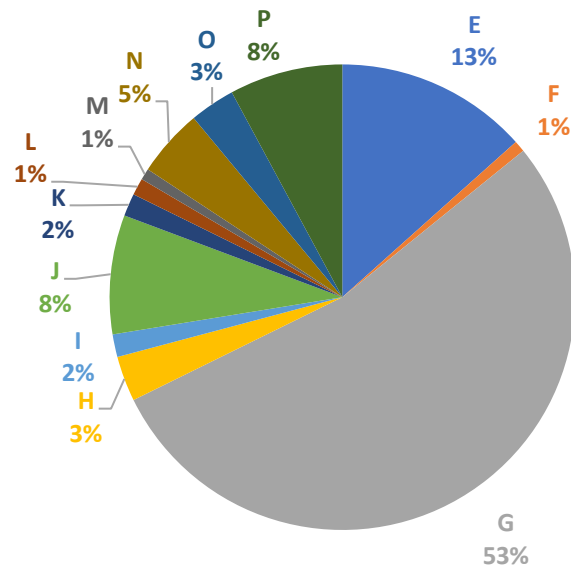


Figure 15 - Selected CVC units favored investment sectors

Operation of selected units

Table 13, below, summarizes how the different units interviewed were structured, shows their fund size and their interactions with their parent companies (“PC”).

Table 13 - Units' structures and operations

Unit	Structure	Fund size	Independence in operation	Independence in investment decision	Frequency of contact with PC	Favored point of contact
Aomori	Independent from PC with dedicated fund (managed by an external partner)	>40m USD	Yes	No	Regularly, at least once a month	Business units
Kagoshima	Independent from PC	>200m USD	Yes	No	Regularly, on a case by case basis	Business units
Saitama	Under the PC R&D department	>50m USD	Yes	No	Every 3 to 6 months	Top management
Nagano	Under the PC R&D department	>30m USD	Yes	No	Regularly, at least once a month	Top Management
Marseille	Under the PC R&D department	>30m USD	Yes	No	Regularly, at least once a month	Business units
Rambouillet	Independent from PC	>250m USD	Yes	No	Regularly, at least once a month	Top management
Yainville	Independent from PC	>50m USD	Yes	No	Regularly, on a case by case basis	Business units

Takayama	Independent from PC	N/A	Yes	N/A	Regularly, on a case by case basis	Business units
Hakodate	Independent from PC	N/A	Yes	N/A	Regularly, on a case by case basis	Business units
Walters	Private firm	>1B €	Yes	Yes	N/A	N/A

The CVC units interviewed were all independent in their everyday operation, which means they had no obligation when it came to their start-up screening process: they had independence in operation. However, the CVCs decision to invest still had to be approved by their parent company's top management, i.e. CEO, CFO or CTO, rarely by the parent company's board members. The following excerpts highlight this situation:

"The decision-making process is quite simple to get the official approval [...] the final decision is not really free but rightfully made me [...] So the boss, the board member delegates function of authority to the general manager and me." A

"We can make a decision by the investment committee, which is the CEO and CTO of the company, and myself" NA

"We present our investments to the investment committee, composed of the CEO, CFO [...] without their approval we won't invest" YA

Expertise on AI

The following table summarizes the level of expertise on AI technologies existing at the units or units' parent companies as perceived by the participants. As mentioned, France and Japan are not recognized today as leaders in AI development. No French or Japanese firm has the influence of companies such as Google or Baidu when it comes to AI expertise. Only one CVC unit, Yainville, did not mention whether it maintained any expertise or knowledge on AI. External partners refer to VC fund partner or large corporations such as IBM or Google, acting as adviser to the unit or parent company.

Table 14 – Participants unit and parent companies AI expertise

Unit	AI expertise at the unit	AI expertise at the PC	Expertise through external partner
Aomori	No	No	Yes (for the CVC unit)
Kagoshima	No	Yes	No
Saitama	Yes	Yes	No
Nagano	No	Yes	No
Marseille	No	No	Yes (for the PC)
Rambouillet	No	Yes	No
Yainville	N/A	N/A	N/A
Takayama	No	Yes	No
Hakodate	Yes	Yes	No
Wallers	N/A	N/A	N/A

The AI expertise of the CVC programs, or of their parent companies is to be put in perspective. While AI did not seem to be unknown to most companies, many interviewees themselves questioned the AI expertise of their companies.

“I think AI is very new for us. [...] We have to know what AI is, what is AI changing and how to catch up the AI activities. [...] I think [the] U.S is three years in advanced compared to the Japanese market (in terms of AI expertise)” HA

“[Our company] work with many other companies than our portfolio companies that are not always start-ups, some of them are bigger such as Google [...] We have a lot of things to learn on AI by working with Google” RA

This situation can be explained due to the very large definition of AI. According to the French bank BNP, this large definition puts “easy” AI task automation processes on the same level as more complex AI technologies, which makes it difficult to characterize an AI expertise (WAI BNP Paribas, 2019).

6.2 Data Analysis

It is first relevant to study where learnings could have potentially happened between the CVC and ventures, using Dushnitsky et Lenox (2005b) learning channels framework. The citations used below were thought to be the most relevant to depict those learning channels.

Table 15 - Learning channels

Location	Example
Due diligence: Screening	<p>"The screening process is all by [our CVC]" NA</p> <p>"When we want to invest in a company, we make an audit [...] If we take the last three years, we worked with 50 start-ups, more than 50. [...] we meet at least 10 times this number of start-up. Statistically, we source around 500 start-ups a year, 50 that we introduce to the different department and 15 in co-development" MA</p> <p>"We see approximately 1000 start-up a year [...] in the end we will do maybe around 10 term-fit. And those 10 terms fit, meaning investment proposal, on the 10 we will win.... maybe half, so five or six" RA</p>
Monitoring: Business meetings	<p>"If a customer or our Japanese team have an interest in [a start-up] solution, I can set up a call, or an operation project, an evaluation inside of their companies. Just a small project to test or evaluate such solutions" HA</p> <p>"Usually, we have a monthly meeting with the portfolio and on a ad-hoc basis we make intro to [our group] companies. So it's very common... It's not one-to-one meeting. They usually host the meeting for the investors" KA</p> <p>"we maintain informal relations by calling them regularly, by speaking to them regularly" RA</p> <p>"Every month or quarterly we talk with [our start-ups]" NA</p>
Monitoring: Performance Review	<p>"... the timing is again twice a year the when we review the portfolio companies financially, we monitor the status of the business as well. So twice a year, we know the latest thing." KA</p> <p>"Monitoring would happen because we ask for monthly report" RA</p>
Monitoring: common projects	<p>"After each investment, my team mostly focused on business development with the invested portfolio companies together with [VC partner]." A</p> <p>"So we did some project together to really build [the product]. In that way, we collaborated and developed like futures service together" NA</p>

As depicted in the table, two learning channels were used primarily by the CVCs. The due diligence process provides a first opportunity for parent companies to learn. By engaging with various start-ups, CVCs had the occasion to learn about the AI market, its business application and eventually its technologies.

Monitoring activities equally provides such opportunity, enabling the CVCs to observe the evolution of their portfolio. CVCs could also engage in shared projects with their start-ups, to the benefits of their parent company.

The only learning channel no CVC mentioned was ventures failure. The only exits that took place at these CVC programs, identified using a CVC database research, concerned IPO or M&A (internal or external).

6.2.1 AI Learning through CVC

The first sub-question of this essay focuses on understanding the impact of CVC activities on AI learning processes. By concentrating on the contribution of CVC units to exploratory, transformative and exploitation learning processes through knowledge transfer, creation and retention, this section tries to measure its impact.

Exploratory learning

This research first focuses on the exploratory learning process. Exploratory learning consists in the ability of a firm to recognize and understand knowledge distant from its knowledge base (Lane, Koka et Pathak, 2006; Szulanski, 1996). Said otherwise, it is the capability to identify and acquire externally generated knowledge (Zahra et George, 2002). In this research context, the exploratory learning process would be enhanced at the parent company if the CVC helped the firm understand and value AI knowledge.

As shown in table 15 above, there are many channels through which CVC units could potentially gather knowledge. However, data shows CVCs mainly gathered knowledge for exploratory purposes from their screening process. This is due to the nature of knowledge transferred, as will be explained further below. CVCs screened start-ups through different means, from interviewing them, searching investment opportunities through the internet, gathering pieces of information from partners, investing in a fund of funds. Quotes from table 15 and below highlight this situation:

“The screening process is mostly made by [our partner] because as I mentioned earlier, we are very humble to reflect ourselves. We do not have any expertise in the screening process. After each investment, my team mostly focused on business development with the invested portfolio companies together with [our partner].” A

“[We] look for news or for like the start-up information from things like CB insights or pitchburg. Each of us [at the CVC] borrow these information’s everyday, and every investment person in the team explore those opportunities. That is one [way we source start-ups]. The second one as mentioned we invest in fund. We did fund of fund activities. We get into internal transaction from the VC to reach out to the more [interesting] start-up.”SA

Learning by gathering information

CVC programs first impacted the exploratory learning process of their parent companies because they facilitated the gathering of pieces of information on AI technologies and AI markets. CVC activities allowed parent companies to explore “distant” pieces of knowledge. This exploration of distant knowledge was a concern for all seven CVC units. The idea of discovering new knowledge was well embodied in the expressions CVC units used to describe themselves, such as “radar” or “homing device”. The following quotes highlight this situation:

“Our direct competitor could be Google FB, Amazon or say Tensen, Alibaba, Baidu and some others tech giants. I personally chase their portfolio. I always chase the invested companies those companies invest in. [...] I always look, make deep dive in why they speak that or they mingle in that story or something.” A

“We have a really wide vision, we are not dedicated on the strategic objectives of [our parent company] in terms of screening. The idea is that there are good tech everywhere and on many subjects. So to have the largest radar so as not to deprive ourselves of opportunities” RA

“We are really on subject a bit apart, that are still linked with [our group]”YA

“We don’t need to wait for all of the seed technologies to move forward but we can explore other technologies together” NA

CVC programs contributed to exploratory learning by trying to understand the AI market, its trends and its evolution. Investing in start-up enabled the CVCs to understand how different markets were

impacted by AI and what AI had to offer for their organizations. It provided hints into which AI technologies were proving successful commercially, which AI technologies might be developed at their organization, or even what kind of AI business model their parent company could take on. In other words, the exploration performed by CVCs informed on potential benefits of AI for the parent company. The following quotes show that situation:

“We give some sort of lighting on what happen in the market, market development, its evolution, that’s it. We are some kind of a window on the innovation market...Well on the market, more specifically on innovation” RA

“Their [AI] technology is really interesting, but we don’t know that they can get the market traction. But through this investment, we can see that how the market accepts their technology. [...] And explore the... or like see the market traction.” NA

“Having a VC team inside a corporate where all work on innovation programs [...] it allows the corporate team to be up with the latest market trend and the latest techs [...]We invest in companies to decipher their business model, understand a market and exchange with the company [...] so it is enriching for us” YA

“In that case, we should know what the business model should be, or what the technology should be implemented. Or what business operation, organization or capabilities we should prepare. So, we have no idea. So, we should first invest into the companies and into what the market glance and what is the competitive analysis context, you know, what capabilities we should take it on. So its kind of understanding the market, understanding the business” SA

“The first three years is very challenging for us because we need to understand the [AI] market itself. But through the experience in some investments, we get the deep knowledge.” SA

Hence, through this vast exploration of the AI market 6 CVC programs could detect AI solutions that could potentially be of interest to their parent companies. They often discovered start-ups with AI solutions which simply did not exist at their parent companies. For Nagano and Saitama, this search for innovative AI solutions tended to be linked to their parent companies core businesses. Their idea was to understand how their companies’ core businesses could evolve. For the other CVCs, the search for AI solutions was more focused on exploring ideas that could improve overall business units’ operations.

“They are using many different detectors and are predicting the color of the traffic signals [through AI]. So that technology is really needed to think about the future and develop the future system.” NA

“So this business is very interesting for us because we learn on [...] information business” SA

“There is another company that uses AI for human resources subjects...of HR management called [name of the start-up]. [...] We invested because it had highly performant HR management tool and high recruitment standard” RA

The seven CVC units facilitated the AI exploratory learning process of their parent companies, as they helped them to discover knowledge the regular parent companies’ R&D teams and business units could not have collected otherwise. In fact, those teams did not have the time nor the resources to do so. Hence, CVC activities increased the *range of potential* AI solutions a company could explore. Said otherwise, CVC activities have increased the exploratory AI learning of their parent companies by amplifying the range of AI knowledge investigated (Lane, Koka et Pathak, 2006),. In a way, parent companies “outsourced” their exploring activities by granting CVC programs with resources (time and money) to research specific subjects, such as AI.

The following excerpts highlight this finding:

“The advantage of a structure dedicated to start-up investments is that it allows [you] to be in an explorative mode, to take a step back and think about subjects the teams do not have time to explore, or don’t have the prerogative to do so because they have a different rhythm...their working rhythm is different because they have to aim for quarterly results” YA

“I work on subject that are not getting addressed by the different business units, or I will come help them, on their request, on subjects that they can’t address due to a lack of expertise or time” MA

Commercial knowledge, technical knowledge

Through exploratory activities, it seems CVC units allowed parent companies to better recognize and understand AI knowledge. Yet, it is relevant to clarify what is meant by recognizing and understanding AI knowledge. Chesbrough (2002) sees CVC as a way to channel knowledge on

“unknown products, services or technologies”. However, CVC AI activities did not channel any technological knowledge. Rather, they have informed parent companies on the AI technologies’ business potential and applications. In this sense CVC activities improved the exploratory learning process of their parent companies, thanks to the exposure to AI technologies they provide (Maula, 2007).

However, CVC programs, through their activities, did not better understand the ventures’ AI technological knowledge. Therefore, they could not transfer this type of knowledge back to their parent companies. The technological knowledge they grasped from their ventures remained at a general, basic level. This situation is especially true for CVCs that reported having no prior AI expertise. Of course, it could be difficult for CVCs to have access to the ventures’ proprietary knowledge such as AI codes. Having access to such knowledge without the ventures’ consent could constitute a case of misappropriation. But in general, the activities of the seven CVC programs have not modified their parent company AI technological knowledge.

CVC activities did not aim at increasing parent companies’ internal AI knowledge. Rather they focused on transferring useful knowledge regarding AI applications, as mentioned in the following citations. Those activities strongly contributed in increasing knowledge regarding what AI could do, exploring new avenues where that set of technologies could be used.

“We have a learning process of each industry, AI, IT or say various industries, these knowledges are very general ones” A

“Our activity did not change anything, in AI context (in terms of AI expertise). But like open innovation or like accelerate the innovation process or think about like new products or innovation, in that sense we changed a lot. But AI context, nothing changed” NA

“It is to better understand the business application enabled by AI. But to understand AI, its techniques, no, that’s not the subject. It’s more understanding the impact it can have on business. By introducing companies that have tools based on AI, it enables [our group] to better understand what it is” RA

Impact of other open innovation structure on AI exploratory learning process

The accelerator program and the research program seem to have produced similar results on the exploration activities of their parent companies. Both of these open-innovation structures explored AI solutions and gathered information regarding the benefits of the ventures AI solutions. They were tools for the parent companies in widening the range of AI solutions they could explore. At the same time, the knowledge these structures exploited was also commercial and not technological. These structures were not used as substitutes for their R&D departments in transferring technological knowledge. They were used, as the CVC programs, to explore commercial knowledge.

“I learned a lot how AI works or what difference [it has] with other existing technologies. [...] I have learned that there are many other things that can be done by AI [...] But it is impossible to you know, to learn everything so I know a little bit about what AI can do but basically that is all. Of course, I have learned that there are many other things that can be done by AI compared to 5 years ago, its speed is getting faster, they can handle more big data than before. But basically, that is all” TA

“we are just researching on AI itself like technologies-side or business-side. [...] I always talk with AI companies what is your business model, what is the use case of your activity. If it matches for Japanese market, I can introduce [these] start-up companies to Japanese enterprise [of our network].” HA

Yet compared to acceleration or research programs CVC units had a greater range of exploration for AI knowledge. Compared to the other open innovation structures, the CVC units were more focused on understanding the trends in the AI market in the long term and were not limited in the solutions they could explore. Besides, investments in CVC units generally occurred at a later stage in the start-up's life compared to the accelerator or research program. At that time, the start-up's business model was mostly completed, and its products could already be launched. By exploring AI solutions that are already developed, if not already proven commercially, CVC programs inform parent companies on immediate AI use cases. In other words, CVC programs helped understand the business model for AI. The following quotes highlight the differences between the programs:

“The acceleration program is sometimes a good thing to bring in, sometime a bad thing to bring in. The pro side is to focus on any specific requirement for example MFG the banking branch of Mitsubishi, BTME ran on the acceleration program for the fintech. [...] The idea was to explore how to help their mobile banking or the online banking solution or solve a security problem. [...] Our idea was different, not a specific idea but we want to know more

long term the trend to understand. In that case, the learning on acceleration program is very niche [...] it is not efficient to understand the new trend, because we should set the topic. In that case, we should see future ideas.” SA

“They thought that this incubation program is really It’s a good way to start lot of new projects together for like POC together, and from these activities we can find really good future core of the business [...] Usually, it took a long time to really figure out make the idea to business. But [our] expectation was [to] make a business” NA

“It is less risky because we invest at a later stage. The advantage of incubating a start-up is to be able to configure the start-up as you want [...] The risk is that it is really the beginning of the story, you need to develop the product. So you have a product development risk. [...] we invest after all this, we invest when the product is made and the start-up is ready to go on the market” RA

Propositions

An important finding in the analysis is that the knowledge being transferred through the exploratory process, from ventures to CVC then CVC to parent companies, is essentially commercial knowledge, or market knowledge. CVC programs have not increased their parent companies’ understanding of AI technologies. However, they explored business solutions and discovered ways AI could be harnessed at the parent company. Therefore, a first proposition can be developed to answer Volberda, Foss et Lyles (2010) call to clarify what kind of knowledge gets transferred between external partners and receiving companies:

Proposition 1: Only commercial AI knowledge gets transferred between partners in an AI CVC relationship.

From the analysis, it seems correct to assume CVC impacted its parent company when it comes to the AI exploratory learning process. By transferring commercial knowledge, CVC activities improved the capacity for their parent companies to explore, identify and understand AI business models. They increased parent companies’ potential for AI discovery, having the time and resources to explore distant AI solutions. Proposition 2 can therefore be developed as followed:

Proposition 2: CVC AI investments increase the range of AI commercial knowledge explored by a company, thus accelerating its understanding of AI benefits and business models.

Figure 16 summarizes the findings related to the exploratory learning process.

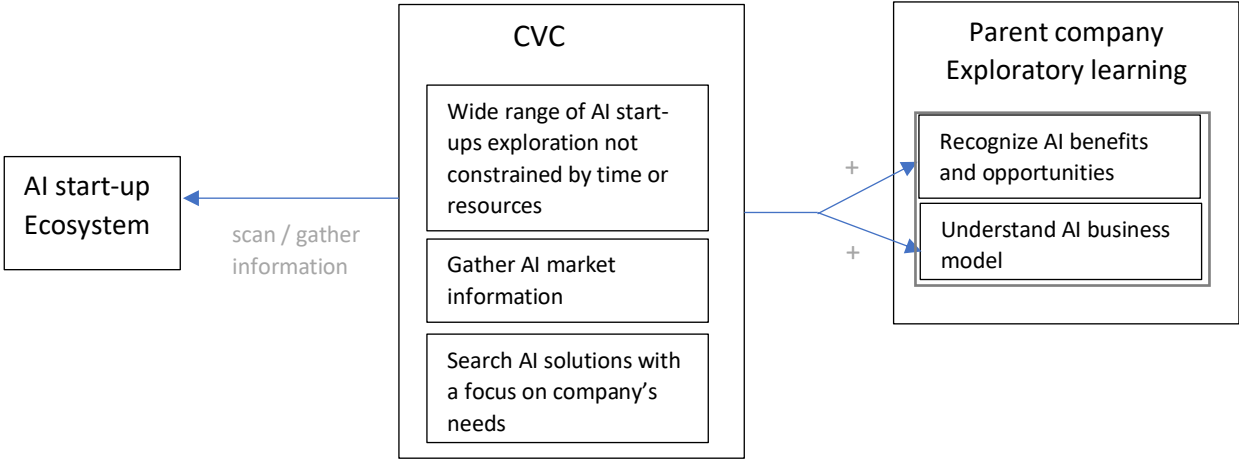


Figure 16 - Impact of CVC on AI exploratory learning process

Transformative Learning

If the exploratory learning process deals with the company discovering new knowledge, the transformational learning process refers to how said company assimilate this new knowledge. Assimilation refers to the internalization of externally acquired knowledge where the latter gets interpreted and processed through the firm’s routines and processes (Lane et Lubatkin, 1998; Szulanski, 1996; Zahra et George, 2002). Knowledge gets internalized through the development and refinement of the firm’s routines that will combine both the prior existing knowledge and the newly acquired knowledge (Zahra et George, 2002). Transformative learning therefore links exploratory learning with exploitative learning (Garud et Nayyar, 1994; Lichtenthaler et Lichtenthaler, 2009).

The transformational learning process deals in how the receiving company learns to integrate and maintain knowledge over time, how it changes its process and rules to accommodate for new

knowledge and learns when to mobilize or not this acquired knowledge (Garud et Nayyar, 1994; Lichtenthaler et Lichtenthaler, 2009). Changes in transformative learning explain why parent companies adapt their processes, their knowledge base and cognitive schemas to absorb new knowledge such as AI (Zahra et George, 2002).

This essay analyzes how CVC activities may contribute to the way its parent company learn how to assimilate external AI knowledge. The data analysis showed earlier that no technical AI knowledge was transferred between CVC units and their parent company, as per proposition 1. Hence, CVC may only be a support in assimilating a commercial, market knowledge.

CVC activities as a trigger of change

Data shows CVCs first supported the assimilation of commercial AI knowledge at their parent companies through their role as “ambassador” of their AI start-ups. They “provoked” the internalization of AI solutions by introducing them to their parent companies’ business units or top managements. The seven CVC units were looking for AI synergies between their portfolio and their parent companies whenever possible.

As mentioned above, all the CVC units maintained structured or informal contacts with various levels of their organizations, from business units’ managers to top management executives. Knowledge transfer between CVC members and parent companies’ members mainly took the form of discussion or meetings. Through these frequent contacts, the units could transfer the knowledge they gathered from exploring the AI ecosystem and AI markets.

CVCs acted as mediator in having their parent companies confront innovative AI solutions to their existing routines and operations. This activity allowed business units to interpret whether they could change their operation to incorporate the AI solutions or whether this AI solution was of any interest at all. CVC programs typically introduced potential AI solutions to their parent companies’ business units before investing in the start-ups. The following excerpt highlight this situation:

“We speak regularly to the bigger operational business units [of the group], and we do it in a structured way. We have meetings every month or two, to exchange one on their needs, and also on our deep flow” RA

“Like every month or quarterly we talk with [the start-ups]. Conduct project together, think about their growth and support them. Collaboration depends on the deal. Usually, we planned before the investment.... Yeah, through our investments we try to figure out what way or how to develop the business together.” NA

“We report to our CEO. The CEO want to know the new trend or the new business. In that case we report to the CEO and to the shareholder board member. Every few months or every six months [...] we report to them as they want to know further detail about our companies, or they want to know the new trends. Then they try to, you know, apply our knowledge into their existing unit operation. “ SA

For six CVCs, this knowledge interpretation and assimilation was mainly the result of formal and informal meetings with top executives and business units’ managers. Only one CVC, Marseille, had launched more initiatives that allowed its acquired AI knowledge to be diffused across its company. While these initiatives were not launched solely for AI, it provided a great visibility for this set of technologies at its parent company.

“One person is an open-for-all showroom. [...] You have to make a reservation [...] you come with your team [...] The person in charge is here to show you the innovations from our partners, our start-ups” MA

“We also have tech events [...] spanning two days, we have around 50 booths that are displaying [our group] innovation, our partners” MA

“So it is quite enriching to see all the innovation from the group and to show people [from this department] how you innovate [in this other department] by using AI” MA

As mentioned previously three CVCs were under their R&D departments and four were independent from the rest of their organization. The four “independent” CVCs had only scarce contacts with their R&D departments. Only one of them reported active, yet informal, relations towards its R&D department. The three “R&D” CVCs were more eager to introduce start-ups to their R&D teams, but they equally connected business units to their portfolio. For both cases, as knowledge transfer only concerned commercial AI knowledge, interactions with the R&D departments were more informative than used for a real R&D effort. The two following excerpts highlight this situation:

“We don’t have establish relations [with the R&D units] but we exchange a lot of information, of market intelligence as one could say. [...] We have informal conversations. I take part in regular meetings with our colleagues from [the parent company R&D group]. Yet, there is not integrated relationship you see” RA

“So, they are research institute within [our] group [...] And there are lot of researchers, AI researchers. And the president of [this institute] really interested in [one of our start-ups]. In that sense, we interact together”. NA

Whether it was to their business units, top management or R&D teams, CVCs made sure introducing AI knowledge from their portfolio would be relevant for all parties. Most CVC programs are driven by both financial and strategic motives as seen in table 11. They have financial interests in making sure their portfolio companies will grow. They also have strategic interests in having their parent companies discover new knowledge and potential business opportunities. CVCs only started discussing with their parent companies or connected their ventures to them if they knew it could bring benefits for both the start-ups and their parent companies. By accompanying the introduction of AI solutions to business units from the start, CVC units made sure changes would happen at their parent companies: it was in their interest to have successful joined projects between parent companies and start-ups. Specifically, CVC programs made sure the business units were on board with changes from the start, by reviewing their business needs. Those needs are not necessarily technological needs, but rather comments on what the business units would like to improve in their operation. This situation is seen in the following excerpts:

“Every April we interview each department of [our parent company] [...] [to see] what is their business goals what could be applicable or implemented by them. The interview is very important. “Know the enemy to win the game”. [...] Id say all departments, all companies have their business mission, business goal. They do not welcome something different or something new. So I say direct merit for those departments would be the keys to be welcomed by them. So we spent almost four years trying to show these merits [that working with start-ups work]. We kept working to prove that it worked. The important point is to find a person who could be very supportive of projects and would be sufficiently influential.” A

“We also interact with the other business units. [...] We can’t invest if we don’t have the opinion of the employees. They know better than anyone what they are doing, so if there are potential synergies [...] we exchange with these people” YA

“Bit by bit, [some people were like] well I have an idea, can AI help us on this subject. And I respond, let’s see [...] [the business units] are not typically resisting change [when we talk to them about AI opportunities]. But they are like “well I was not expecting AI on this to be fair”” MA

“I or my colleagues introduce this start-up to [the group] or any entities group which we think will want. Then, they consider. If they are interested, the business discussion start” KA

“My role is really to be the middleman between a vast, really vast and complex corporate world, often really difficult to understand, and facilitate our start-ups life in interacting with the group business units. [...] We work with the companies in which we have invested, we introduce them [to the business units]” RA

Hence, CVC programs facilitated the transformational learning process of their parent companies by first pushing AI solutions to be applied at their parent companies whenever possible. It was in the CVCs own interest to do so, as they had to answer their financial and strategic objectives.

Changing processes and routines to integrate AI

Another aspect of transformational learning is the capacity for companies to change their existing processes or cognitive schemas to integrate new external knowledge (Zahra et George, 2002). Changes to existing processes are known as the process of “bisociation”, which is a part of assimilation. Bisociation occurs when organizations come to understand situations and ideas that were initially thought incompatible with their existing operations and processes, by changing their processes and cognitive schemes to welcome external knowledge (Zahra et George, 2002). A change in processes and routines might lead the way to a greater assimilation of AI knowledge.

Four parent companies experienced to a certain extent “bisociation” that was initiated by their CVC units, as shown in the table below.

Table 16 - Bisociation at the CVCs

CVC unit	Initiatives implemented	Quote
Aomori	<p>Reviewing processes, analysing where AI solutions could be integrated to current operations.</p> <p>Example at the PC: Rethink price calculations by integrating an AI-driven solution for generating price prediction for major projects</p>	<p>“So, all departments including [our CVC] need to conduct business re-processing. Machine learning and RPA could be the easiest ones to be implemented in these various processes. No division, no departments welcome or be negative in AI. All departments are very positive of AI. “</p>
Saitama	<p>Accompanying business units in operationalizing AI solutions and implementing AI processes.</p> <p>Example at the PC: Rethink real-estate valuation process by including automatic AI price evaluation.</p>	<p>“because it is an experiment, because it is a trial [we say to the business units] why not choose this product then we can support you and we can bridge you into the portfolio companies. [...] So this is why we help, we stand between the business units and the start-up to help make things smooth”</p>
Marseille	<p>Create new processes to accommodate the arrival of AI solutions at certain business units.</p> <p>Modify current know-how and know-what to include AI solutions.</p> <p>Example at the PC: accommodate customer services processes to include AI-driven chatbots</p>	<p>“it creates problem when it comes to processes in the sense where processes do not exist [...] we reverse, we have to reverse processes [...] [for example], we are doing it right now on data access”</p> <p>“We support our teams [through this process], even the digital ones that are used to change and innovation. Why because we are not attacking the business units but the expertise. And that’s quite hard. They are not resisting this change [...] but they are like “oh, I was not expecting AI on this”. It’s more of a surprise but after it goes well. There is still an initial shock”</p>
Rambouillet	<p>Engaging with business units in process changes to rethink how business units are operating by replacing human operations by AI solutions.</p> <p>Example: Cyber subscription for security, AI HR platform for faster recruitment.</p>	<p>“AI allows us to do things more efficiently. Fraud detection, financial advise, etc. [...] We invested in a company that does risk analysis [...] they are capable, based on data sets they analyse, to say “here are the weak points and the attack risk of this [web]site” [...] The operational teams of [the parent company] now have access to this data platform. Through this, it allows them when they take a cyber subscription risk to have access to data, data they did not have before”</p>

Some CVC units also created a change in how AI was perceived at their parent companies, a change in cognitive schemes. By interacting with the different business units and the top management, and by transferring market knowledge, CVC programs “introduced” how the AI solutions of their portfolios could suit business solutions and modify the “myths” surrounding AI technologies (complexity, cost, etc.).

“[The] operation level or the field engineers feed the business operation guys to understand our start-up, our portfolio companies to use in their daily operations.” SA

“We did presentation, acculturation to say here’s what AI can do for your departments” MA

“[Working with start-up] allowed to [...] demystify the AI subject, to make it accessible for everyone [...] It was the start point, the foundation stone, it started a fire with concrete results [...] I am not talking about something vague where you need 15 data scientists to explain what is a neuron network” MA

“By introducing companies that have tools...based on AI yes of course it will help [the business units] to better understand what it is” RA

Despite the changes in processes and perception described above, it is impossible to say with certainty whether CVC activities had a substantial impact on the companies’ capacities for bisociation. It is also not possible to measure the extent of changes that occurred on their parent companies’ processes and routines following CVC activities. First, of the seven CVC units, three did not mention any change to their processes and routines. In addition, the modification of processes at the four aforementioned parent companies mainly took place to accommodate case-by-case AI solutions integration. Changes in processes and routines did not occur systematically at the parent companies. Parent companies did not learn how to change their processes and routines to welcome, create or research further AI technologies for their operations. They only learned to change processes at specific business units for specific AI use cases. The integration of external AI solutions was simply seen as collaboration between partners, where business units became “users” of start-ups’ AI solutions.

Retaining AI knowledge over time

Another key aspect of transformational learning is the capacity for a company to maintain the knowledge it acquired over time, to keep it “alive” for future use (Lane, Koka et Pathak, 2006; Lichtenthaler et Lichtenthaler, 2009). Knowledge retention is a crucial sub-process of organizational learning, as knowledge does not persist through time (Argote, 2013: 58).

Only Rambouillet reported having a specific system to maintain the AI market knowledge it acquired through time:

“We see a lot of start-ups. Many in which we invest, some in which... Many in which we don’t invest. But they could be relevant. Not for [the CVC], but for [the group]. We

developed a tool [...] that you can find on our [internal] website which is some kind of a database of all the start-up we see” RA

This knowledge retention system only occurred at the CVC unit but not at the parent company. However, all employees from Rambouillet’s parent company had access to the commercial AI knowledge database.

For the other CVCs, it is reasonable to think their acquired commercial AI knowledge resided at the individuals’ level. Presence of similar start-knowledge databases at the CVC units or the parent companies was not shared by other respondents.

Not maintaining this CVC AI knowledge may not have such a deep impact for parent companies. Knowledge acquired through CVC deals mostly with AI market information, AI use cases, applications and opportunities. The acquired knowledge may not be relevant in a long-term and might not be reused. Saitama for example reported the dynamism and changing nature of AI technologies and markets.

Pieces of knowledge that could have been reactivated and synthesized for future use, i.e. AI technological knowledge, are not transferred to the parent company. Only those pieces would have had to be maintained for future use. Therefore, CVC programs do not contribute to maintaining acquired AI knowledge, because knowledge acquired through AI start-up portfolio can seldom be reused.

Learning to Choose AI

Another aspect of transformative learning is the capacity for firms to choose certain technologies and products, to choose “which path to follow and which ones to abandon” (Garud et Nayyar, 1994). This reality was encountered at five CVCs. In the case of Kagoshima, CVC activities even led to the parent company stopping an internal R&D project to choose the technology developed by a start-up:

“[our group] was developing speech recognition function by themselves but they saw some advantages in other start-up technologies that is why they decided to use this instead of their own effort.... [...] Of course, they were developing it by themselves, but they saw some differences and some advantages.” KA

“We worked with an important American start-up on our website, it creates automatically your web page. You give [the AI] your objective, click rate, transformation rate [...] you give him the colors, what it can do, the text [...] We did the test on one million client on [our] website and in three weeks we made an additional 10% in transformation rate, which is colossal [...] aesthetically speaking it is less pretty, but it is way more efficient” MA

“[our company] has many technologies that are really prevent the copy really they use to develop the detecting fake builds. There are certain aspects [(of the start-up technology)] that we can use. In that context we invested in [the start-up]. And together with [the start-up] we are thinking to start some kind of project together.” NA

“[our group] was developing a solution by itself on a new product. This development was long, complex and the obtained result was not going to be as high standard as needed be in order to sell it in the market. At the same time [the CVC] found an excellent partner on the market to could bring the foundation stone [the parent company] could not build as efficiently as the start-up did. On a win-win model, we studied the opportunity of investing in this start-up” YA

“[we] are an accelerator in investing in good ventures, introducing them and accelerating the decision process of [our parent company] to work with them [...] So we are a contributor to the acceleration of [our parent company]” RA

Two CVC units’ activities (“R&D” CVCs) even led to the creation of AI labs and AI research programs at their parent companies. CVC activities provided information that made their top management consider the potential impact of AI on their core activities. CVC programs contributed in making the top management realize the necessity to acquire proprietary AI technological knowledge, through having them assimilate commercial and market AI knowledge. As they could not transfer technological knowledge from ventures, they decided to create their own proprietary AI knowledge by developing AI technologies they fought the most interesting based on AI market knowledge they previously gathered. Therefore, it had an impact on the companies’ technological strategies. This situation was not reported at “independent” CVC structures. More data is, however, required to confirm the impact of the different CVC structures on transformational learning.

The following two examples highlight how CVC start-up activities contributed in redefining the technological strategy of their parent company:

“The background of the establishment of this lab was inspired by our AI investment so actually in 2014 summer [...] So then, I understand that investing in AI companies is a good

way to understand the market [that] AI brings a huge impact for us. [...] In that case, we should focus on implement[ing] our proprietary AI. So not going for the investment but by ourselves. So, then we realized, me and my colleagues, [we needed to ask] the CEO to establish our AI lab. We did so to share the knowledge [from] our investments to the CEO. Then the CEO easy[ly] underst[ood] the requirement of this fund, this lab, [we] establish[ed] this lab..." SA

"I went to see the CEO, told him it's been a year we have been working on AI, here's what have been done. It's great, all the business units have been impacted...But it's just DIY, now we need to speed up, we need to work on more complex thing that can't be done by start-ups, we don't have the capabilities, we need help to speed up the subjects [...] on our core competencies" MA

Transformation learning triggered by other open innovation structure

Similar to the CVCs, the accelerator program provoked a change in transformational learning by pushing AI solutions to its parent company's business units.

"I share those documents or their information to our colleagues [...] I will try to make the meetings between those start-ups [...] I [arrange] lots of meetings between start-ups and our colleagues or corporate partners [...] So I just push to my colleagues in France or Singapore or many other countries. If they find synergies with the start-up they will connect to the right guy." TA

Hakodate also introduced start-up solutions to its parent company:

"If it is good [(the start-up)], I think it is good I'd like to introduce them to the Japanese market. And there is a Japanese marketing team in Japan. So they catch the items. Also they are talking to other business divisions." HA

Differences between those structures and CVCs first has to do with the units' objectives. To ensure they invested in the right start-up, get the support from the business units and have their portfolios grow, CVC units tended to start working with their parent companies from before having invested in any specific AI start-ups. On the other hand, the accelerator and research program introduced their start-up portfolio to the parent companies after start-ups were on board their respective programs.

“many of the start-ups that apply to the program are interested in working with [our parent company], in some ways. So, when they join in the program, I share all the information with my colleagues in France” TA

“I contact with [the start-ups] directly. They provide information for me. If it is good, [if] I think it is good I’d like to introduce them to the Japanese market. [Also] there is a Japanese marketing team in Japan. So [the marketing team] catch the items [, the start-ups information]. [Then, the marketing team people] are talking to other business divisions.” HA

CVC units were therefore more able to trigger changes in the transformational learning process of their parent company by more carefully selecting start-ups and seeking the approval of business units.

Propositions

CVC programs have contributed to their parent companies AI transformational learning process to a certain extent, by having them assimilate some portion of AI knowledge. First, CVC contributed to the assimilation of AI knowledge inside their companies by forcing changes. By pursuing its own objectives, strategic and financial, CVC activities multiplied opportunities for external AI knowledge to mix with their parent companies existing knowledge and business operations: it was in the CVCs interest to have their start-ups efficiently work with their parent companies. This finding led to the development of proposition 3:

Proposition 3: CVC investments triggers the integration and assimilation of AI solutions at the parent company

It is important to note the knowledge assimilated by parent companies was mainly commercial knowledge, which explains in part why CVCs did not contribute significantly to AI knowledge retention. CVC units transferred knowledge to their parent company on a case-by-case basis, only when they saw fit and in the interest of all parties. The commercial knowledge acquired through AI start-up portfolio could seldom be reused and therefore was not maintained by the CVCs.

Proposition 4: CVC investments in AI do not lead to any AI knowledge retention at the parent company, as commercial AI knowledge seldom gets reused.

The analysis did not find sufficient support on the impact of CVC activities on bisociation activities at their parent companies. Only four CVC experienced such change, hence more data is required in this field. On the other hand, the analysis showed CVC programs “guided” their parent company decision process to abandon some of their R&D projects, or to integrate external solutions to their offerings. For some CVCs, it even influenced the companies’ technological strategy. In other words, CVC activities helped their parent companies learn when to use or not AI external solutions.

Proposition 5: Investing in AI start-ups through CVC guide the parent company in their technological and strategic decisions-making, helping it decide when and where AI knowledge should be used.

It is important to note that the impact of CVC programs on transformational learning described above is not unique to AI solutions. CVC programs have highlighted AI was no different from other technological investments in this situation. But a key point is that CVC activities allowed parent companies to introduce AI solutions to business units that had not necessarily expected AI technologies to support them in their everyday workload. The interaction between CVC programs and business units allowed to uncover business needs that could be filled by AI technologies directly, for example re-designing website, improving the recruitment process, etc. The presence of a CVC program has thus greatly accelerated the introduction of this set of technology, which remained unknown to most at their parent companies, and began an AI assimilation process.

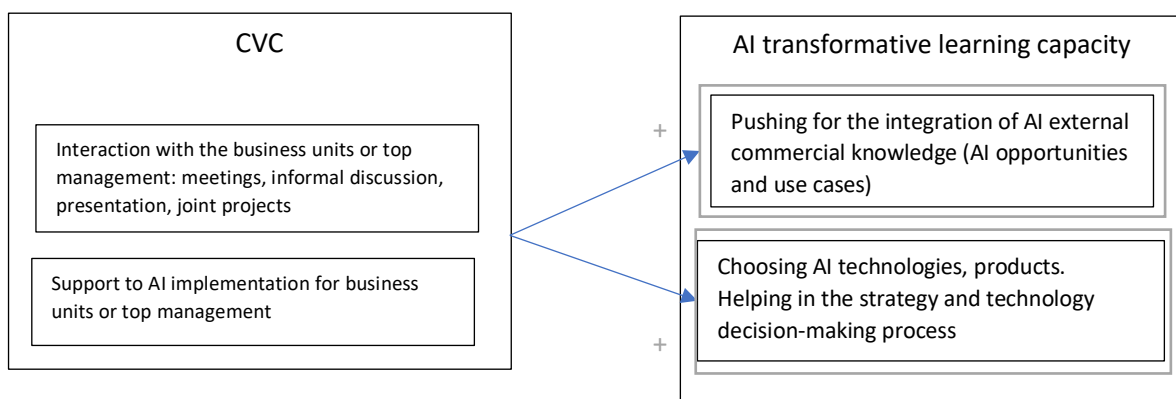


Figure 17 – Impact of CVC on AI transformative learning process

Exploitative learning

The exploitative learning process refers to a company learning to apply externally acquired knowledge for new knowledge creation or for commercial outputs (Wesley M. Cohen et Levinthal, 1990; Lane, Koka et Pathak, 2006). For Zahra et George (2002), this capability allows firms to refine, extend and leverage their existing knowledge by using and implementing acquired knowledge into their operations. In this research context, CVC activities would increase their companies AI exploitative learning process if they develop avenues to access and reuse the start-ups AI knowledge in order to create or exploit AI knowledge.

Up to this point, the analysis showed CVCs helped uncover, through exploratory learning, a wide range of AI solutions that may be interesting for their companies. It also exposed that transformative learning made the parent companies more able to understand when and where AI could or should be used. In this section, it will be seen that CVC programs helped create an experience in working with AI solutions both at their unit and at their companies. The parent companies learned how to *realize* or exploit the potential AI opportunities discovered previously.

Experience through experimentation

CVC activities first provided parent companies with the opportunity to experiment with AI knowledge. Six of the seven CVC programs reported having experimented with novel AI technologies. This finding is in line with Cassiman et Veugelers (2006) and Basu, Wadhwa et Kotha (2016: 210-211) argument that CVC may enable firms to try new technologies. If it were not for the CVC, those experimentations with AI would not have taken place and companies would not have gained this experience in testing potential AI solutions.

Experimentations took the form of common projects between ventures and parent companies' business units. It is relevant to note that business units involved in these joint projects did not have access to the start-up proprietary knowledge such as the AI codes. Therefore, they could only experiment with the AI solution provided directly by start-ups, whereas they understood AI application.

“We have dozens of projects in a year, relying on start-up to do some AI. It went from the legal department, predicting litigation cost, to the HR department, to better sourcing résumé. [...] It was really vast, the objective was to show each department that AI was not that difficult to implement” MA

“[For the business, we can share the same kind of vision. And also [our company] has many technologies that are [...] use[d] to develop the detecting [of] fake build. There are certain aspects [of the start-up technology] that we can use. In that context we invested in [start-up name]. And together with [the start-up] we are thinking to start some kind of project together.” NA

“The company is to establish model of Reinforcement learning (not deep learning). The company and some divisions of [our parent company] conducted several concept projects including direct pricing in [one of the group] division, price prediction for [...] projects [...] in Tokyo.” A

Experience in sub-contracting AI needs

Beyond experimentation, CVC was a short way for companies to start exploiting AI technologies, as “users”. By relying on external partners, parent companies could subcontract their AI needs and develop AI commercial solutions way faster.

“Investment does not lead to learning, its just acquiring a technology from our side [...] if they want external technology, they ask us CVC team to look for companies. [...] First example to “use it” was that the AI start-up provides AI-based solutions and [our group] paid the licence fee to use it. And just used that technology. So, the technology was not integrated into [our] services at all” KA

“We typically, after our investments we use their product into our existing business to improve our productivity. Then we understand not only for the knowledge but for our experience what the AI bring the benefit for our business” SA

“Of course, they will gain capabilities by working with experts [...] But the problem is whenever you start sub-contracting, you don’t have any internal expertise. You will have the [start-up] employees at your company, [your employees] will gain capabilities, they will learn new services, it can give them new ideas for their own culture but then....” WA

As mentioned in the literature review, research in AI is currently ahead of business application (Ransbotham *et al.*, 2018). By applying AI solutions through start-ups, companies mitigated the risk of experimenting with AI while diminishing their R&D costs. At the same time, parent companies

gained experience in having AI solutions launched into commercial outputs. Through CVCs, six parent companies could refine some of their existing technologies or produced new commercial outputs. The following excerpts show this situation:

“[The group] launched the service brand [XXX] in January 2017, leveraging [the start-up] semantic search engine. [The group] is the licensed exclusive reseller of [the start-up] products in Japan. [The service XXX], which has been improved through integration with [the start-up] AI technology and [the] Group solutions, offers a customer chat-support system and FAQ database-generating service. With this investment, additional functions for connecting to various SaaS solutions are anticipated in the future.” KA

“Through this investment, [our group] aims to support [the venture] to grow the business and improve the quality of the services” SA

“For a big company it is really interesting to use start-ups [to develop AI solutions]. It saves time, it does not have available teams, does not have the agility [...] start-up are in a “commando” mode, goes way faster” WA

AI start-ups were also used as a way to subcontract part of the parent companies’ R&D effort to leverage their existing knowledge. Parent companies would integrate external AI technologies into their R&D efforts to fasten their innovation process, although R&D teams did not have access to any AI proprietary knowledge. Their R&D technological need was previously identified, and no change was required to exploit external technological knowledge. Therefore, start-ups knowledge fitted research efforts, but could not be reused for subsequent innovation development (unless the CVC or parent company once again called upon the start-up services). Such situation was encountered at Nagano and Kagoshima.

“We used their technology and applied to AI controller development. There’s one successful case to include the start-up AI technology to [our company] product.” NA

“[one of the] companies was providing their own solutions. At the back of that solution, one of the core was the start-up technologies. So they integrated that technology at the heart of their own solutions [...] In that example, that start-up technology improved the technology right. With their innovative technology.... so in that sense it led to innovation.” KA

“What was in it for companies to invest in [my AI start-up]? Well, they didn’t have the internal tech resources...All of this takes a lot of R&D, and it’s not their core solution, they

have no incentive to do it internally. Better do it via a company, a start-up that does this, that will support them and offer them a service they don't have" WA

Re-using AI knowledge for R&D and knowledge creation

Therefore parent companies, through their CVC activities, learn how to exploit AI technologies faster by relying on external partners or by starting to experiment. However, as said previously they were unable to extend their AI technological knowledge base.

As CVC activities only transferred AI commercial knowledge, it hindered the ability for parent companies to create subsequent associations between their existing knowledge base and the external AI knowledge that was acquired. Said otherwise, as parent companies did not have access to any proprietary AI knowledge, they could not access technological knowledge for future usage. This situation has a direct impact on knowledge creation, as parent companies could not reuse any of the knowledge transferred from CVCs. Their capacity of reusing, reassembling AI knowledge did not change.

It is therefore not surprising to see that the data shows a clear difference between the increased capacity of parent companies to use and apply AI solutions, and their unchanging capacity of developing new AI technologies or new AI applications on their own. Said otherwise, parent companies only gain experience in using and applying outsourced AI technologies through their CVC activities.

An avenue for M&A

Yet, CVC programs might have an impact on future knowledge creation. As previously mentioned, investing in promising start-ups enables parent companies to evaluate different AI solutions without having to spend heavily on R&D expenses. CVC activities gave parent companies time and information to gauge whether AI start-ups technologies are interesting for their operation. At the same time, investing in start-ups secured and protected the relationships with ventures, as confirmed by the quote below from Wallers. Ultimately, CVC programs provided an avenue for M&A if their parent companies wished to acquire innovative start-ups solutions. By acquiring start-ups, parent companies could have access to their knowledge base, including technological knowledge.

CVC programs can therefore also be seen as a “build-or-buy” informants for parent companies. In acquiring start-ups, parent companies might then expect potential knowledge creation and further AI organizational learning. However, further research would be required to confirm this relation. While some of the CVCs’ had acquired start-ups from their portfolio in the past, none of these start-ups operated in AI.

“If you are still a minority investor you can not learn anything from that company you have to equally partner with them, and if they want modification, they have to ask them to modify it and modifying product will be provided for the integration. So, in that sense they can not learn anything from modification. If you want any confidential information, you have to acquire it. [...] If you want to modify a product, they need to acquire the company because it depends on the IP [...] [for example] [this other company]’s strategy is that sometimes [they] initially [do] minority investments and if they really want that company then afterwards, they acquire it..” KA

“what’s useful is either to invest for a ROI, or to do strategic investments in a build or buy logic [...] to have a 360 view of what’s happening in the market, in start-ups. And if required do partnership or acquire [the start-ups], this is really good” RA

“For the entrepreneur, the moment you let a corporate enter your capital, the risk is that you get blocked on your exit, you can’t sell to the competition. So, say for example Carrefour enters your capital... you’re happy and everything. But you can be sure Leclerc will never buy your company. Because Carrefour will block you, so then you will be forced to sell the rest of your shares to Carrefour” WA

Internal R&D efforts and CVC exploitative learning

In general, they were other ways for the parent companies to learn how to exploit AI technologies other than relying on start-ups. Two of the companies interviewed for this research were for example helped by “big tech” companies to outsource their AI needs. In addition, each parent company in this research sustained its internal R&D effort. However, the majority of respondents pointed out the limits of these efforts. For them, working with other large companies or relying on internal R&D was not sufficient to respond in time to their companies’ innovation needs.

Internal R&D efforts were thought to only answer the core business development needs. At the same time, working with large companies only allowed the parent company to develop an early AI expertise to support their internal and core R&D efforts. But working with start-ups was thought to

allow the parent company to accelerate its exploitation of innovative solutions outside its core businesses. For example, some start-ups solutions from the CVC portfolio helped the parent companies improve their recruitment process, their pricing processes or their customer-relationship services. Those solutions would never have been developed otherwise due to a lack of financial and time resources. In this context, the respondents stressed their parent companies needed to work with start-ups in an open innovation scheme to accelerate innovation.

“A group, be it the most innovative, will never be as agile as a start-up....It will always be running behind on certain segment [...] Because we are on different rhythm, on different decision-making processes, on different budget” YA

“Probably if it is really related to our core business [...], if you want to use AI to those things, probably [our company] can do it by themselves. But for... like I said if you want to find the pipes underground or a program for buildings... there are many many use cases for AI, thousands of use cases. [my company] cannot develop everything.” TA

Exploitative learning at other open innovation structures

Accelerator and research programs provided similar exploitative experiences to their parent companies. In a comparable way, these open innovation structures could accelerate the exploitation of external AI solutions by outsourcing commercial or research needs:

“And next week, I go to Europe and I have to meet with my colleagues who are now trying to implement an AI Start-up service in France for insurance companies.” TA

“[Our company] has its own AI platform, we are using [name of the platform]. [The platform] has many functions but there are missing points providing total AI solution for Japanese enterprise market. [...] I can search for such missing pieces to solve. If I find it, I can integrate it to our AI platform to use [the start-ups] solution” HA

Differences in exploitative capacity between these programs and CVC units came from the relationships they created with ventures. CVC units seemed more able to mitigate the risk for their parent companies to work with start-ups compared to other open innovation programs. By investing in start-ups, parent companies can on one hand mitigate the risk of using new external knowledge. On the other hand, they can block the competition from working with their portfolio, securing

promising pieces of knowledge and technology. Both the accelerator and research program had not invested in any of their start-ups. The following quotes confirm this finding:

“Every time we invest, which is why we have few investments, it is to secure business with the start-up. Let me give you an example. We worked with a start-up that managed the electricity bills of our antennas. In six months, it goes bankrupt, no problem, it is not going to endanger our business, I can find another [one]. However, we worked with a start-up when we launched our internet box [...] We heavily invested to secure this business and increase the number of people working there” MA

“So, of course we need something special by investment. We have different added value [...] The best one is exclusivity in Japanese market or something similar. Or, non-exclusivity for our competitors. Or, if that business contract needs some cost for start to develop something special for [the] group, then we will fund it as an investment. Yeah, in many cases, but we have to have those kinds of values we can not get without investment.” KA

“[when you sign a deal] there will be four documents to sign in general. There is a term sheet that will summarize all the collaboration terms. Then there will be a shareholder pact [...] we will say there is a non-competitiveness provision, exclusivity provision, a clause for... well we’re going to list of the relationship terms” WA

CVC present the advantages of bridging two different worlds, the corporate world and the venture’s world, with increased security compared to an acceleration or research program. CVC activities are the translator between an agile world of start-ups and a more static corporate world. On one hand, a CVC program can follow its portfolio performance at the ventures’ pace and participate to their growth. On the other hand, through its links to its parent company it can connect both worlds.

“I found most corporations including Intel, Sales Force and Cisco, also struggle with corporate politics and decision-making process and how to work with the relating division of the parent company. So how to make quick decision? It is one of the key components to get the CVC activities along with paid, with the timeframe, the world of start-up. They are very quick and fast. They do not care about any lengthy process” A

“It is complicated for a big company that does not have the same culture, the same agility as a start-up, to integrate start-up. That’s why there is a such a high failure rate when a big company wants to integrate a start-up, because it’s not the same mindset, you have to take decision more quickly, it requires agility, in general you don’t have the same corporate culture” WA

Propositions

CVC activities address a need of applying AI knowledge more rapidly and more broadly, rather than having to rely on companies' own internal knowledge base and R&D effort. The analysis suggests CVCs acted as a tool for parent companies to learn what, where, when to use and exploit external AI solutions. CVC only contributed to improving the capacity of parent companies to learn how to apply external AI solutions. Proposition 6 was developed as follows:

Proposition 6: Investing in AI start-ups through CVC can help a firm gain experience in exploiting AI solutions through experimentation and sub-contracting.

However, CVC activities have not contributed to the parent company's learning of AI technologies themselves. Parent companies could not reuse start-up AI knowledge over time to create other innovative solutions or sustain their research effort.

The only solution to access AI technological knowledge would be for the parent companies either to acquire promising start-ups previously identified by CVCs or, as mentioned in a previous section, to reorient its technological strategy following CVCs recommendation.

Proposition 7: Investing in AI start-ups through CVC does not directly impact the ability of a firm to create AI knowledge.

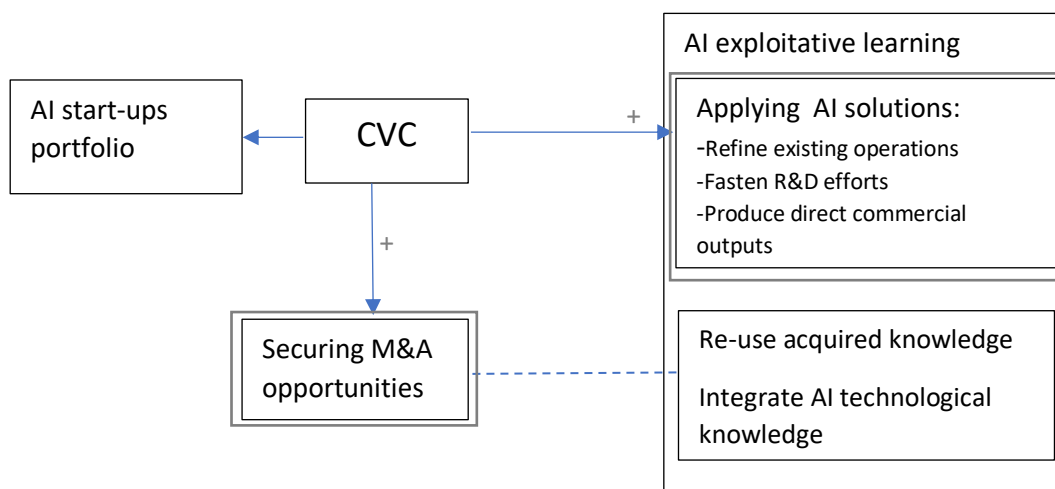


Figure 18 – Impact of CVC on AI exploitative learning process

6.2.2 Influence of AI ambiguity

One of this essay's sub-questions was to understand whether AI ambiguity had an impact on the AI learning processes of CVC relationships. For an AI organizational learning to happen at the receiving parent company, there would first need to be a knowledge transfer between the different units involved in the CVC relationship: the start-ups, the CVC program and the parent company. A successful knowledge transfer would mean to identify useful knowledge, then transfer it back to the CVC and parent company. At that point, knowledge creation or knowledge retention could take place. AI ambiguity could also hamper how CVC unit learn how to explore this set of technology, or how to transform acquired AI knowledge. On one hand, the nature of AI could make it difficult to learn how to integrate and transform AI knowledge, and, on the other hand, it could be difficult to learn how to exploit a complex set of technology.

AI ambiguity

For seven of the 11 respondents, AI had the characteristics of an ambiguous piece of knowledge. Participants either referred to AI's complexity, its tacitness or its specificity as illustrated by the following quote:

« AI came with a complicated vision, it is complex, it is difficult, you need 150 data scientists for more than 15 years and must spend 1,5 billion to do AI. Yes, this is true.” MA

“It takes a lot of R&D to develop AI. It could take years of R&D, it depends on the AI, it can mean anything” WA

“AI is one of [...] different complexity, we deep dive into the technology due diligence. Each expert from our existing business unit and each investment rep [needs] to deep dive into each industry and each technology [...] We also invest in the new technologies or new business models, like AI, blockchain...but these markets are very new for us” SA

“To compete globally, the company must figure out ways to combine user information to its apps, websites, payment platform [...] and develop algorithms that use the data to deliver new services, according to its CSO [...] It puts [the company] in direct competition with the big global players in one of the most expensive labor markets in the world, where annual salaries can top \$1 million: AI software engineers” Newspaper article - SA

Yet, all AI technologies were not considered equal in their complexity and specificity. As explained earlier, AI is an encompassing set of technology, with huge gaps in complexity between the different technologies. For the respondents, it was impossible for them to characterize all AI technologies as ambiguous, as it may have been true for some technologies but less for others. Some technologies are already commercially proven and accessible (NLU, speech-to-text, text-to-speech, ML) while other are still undergoing research and development (deep learning, vision, etc) (Burgess, 2018). The following examples reflect this view:

“When we talk about AI, it brings together many different realities...”RA

“AI, as it is today, is really a catch-all term” YA

“AI is a business buzz word. You need to divide the technologies and the industries of AI into sub-categories. For example, machine learning, deep learning, RPI etc. Each sub-category has each character. Its features that could be the point where each sub-division could be applicable or implemented. For example, deep learning is not commercialized yet.” A

An absence of technological knowledge transfer

Despite differences in the different AI technologies, it is reasonable to think CVC units may have been confronted to AI ambiguity at some point. In fact, the seven CVC units have all invest in several AI start-ups exploiting various AI technologies (several being ambiguous). It may be logical to think AI ambiguity might have had a negative impact on the organizational AI learning of CVCs.

Yet, no CVC units reported coming across any major challenges either in understanding this knowledge, nor working with start-ups involved in this set of technologies. The respondents were not in a situation of knowledge ambiguity such as the one described by Szulanski (1996) as “Lack of understanding of the logical linkages between actions and outcomes, inputs and outputs and causes and effects that are related to technological or process know-how”. Through their relations to the start-ups, and despite observer right or board memberships or frequent communications, investing in AI start-ups did not lead to any major challenges in *transferability* for the different participants.

As per proposition 1, the seven CVC programs did not acquire any pieces of technological AI knowledge at any point. The main technological frame, the technological expertise, any information regarding AI technological pieces of knowledge remained in the ventures' knowledge base. As a result, there was but a few AI technological knowledge transfer: CVC units were not looking into the AI technological knowledge when investing in start-ups, they only gathered *general AI knowledge* that was easy to transfer and not ambiguous. Even during joint projects between the ventures and parent companies, the nature of AI did not cause any problem. CVC units mainly invested in AI technologies that already provided commercial solutions, that did not require further R&D efforts and that could already be applied to their operations. The following quotes highlight this situation:

“To the extent that we did not invest in companies where...their value is a special AI technique...then we did not have any problem understanding...Any challenge understanding what they were doing” RA

“It's really clear what they can bring and what we can bring. They are bringing software and we are bringing hardware.” NA

Therefore, the nature of AI did not impact how learning occurred through knowledge transfer, knowledge creation or knowledge retention. CVC activities, far from being impacted by the characteristics of AI, gained traction because they could bypass them. CVC offered a platform for parent companies to approach AI without having to deal with its complexity, as shown by the following quote.

«You can also do AI quite quickly and I wanted to show, that was the objective [...] that AI was not R&D only, it was for everyone, for purchasing, HR, etc. [...] and you do stuff rapidly with an immediate ROI” MA

In this sense, the interviewees did not experience any differences between AI and their other technological investments. For them, challenges in AI investments were not pertaining to the technology itself:

“We evaluate the technology and what kind of value they can create so it's not really different from other start-up due diligence” NA

“If we have a challenge in particular, it is not related to AI.” RA

An impact on exploratory learning processes

Nevertheless, AI ambiguity was not without any impact on the learning processes. Specifically, data suggests AI specificity had an impact on the exploratory learning process.

In the investment market, many start-ups label themselves as “AI provider” to make themselves more attractive to potential investors. For investors, it becomes therefore difficult to verify whether start-ups are offering AI solutions:

“[The AI start-ups] are in demand, there is always massive competition when you want to invest in an AI company... there is a lot of competition in general but AI is so large you know, there is AI in all economic sectors. There are many funds that wish to invest in promising companies” WA

“Often start-ups say “yes, we use AI to do this and that”. You have to understand what they mean, what they are referring to when they talk about AI” RA

A CVC unit, not interviewed for this research, expresses the situation this way: “[as the definition of AI applies to a vast number of technologies], all technologies “merge” and investors (poorly qualified on the subject) have no way of making the difference [whether the start-up offers an AI value].” (WAI BNP Paribas, 2019).

For CVC units, it can therefore be difficult to explore external AI solutions and properly identify the real AI start-ups. This specificity hinders the screening process, leading to the units having to “guess” whether the start-ups are offering proper AI solutions.

“The ideal case is that [our parent company] has a clear idea about AI. Like I want this this as part of an AI strategy. Can you find any start-up that provide such option? That is the ideal world. It never happens. They do not have a very clear view of AI strategy. They have very very vague view of AI. “I want to do something like this, something like that”. But I don’t know for sure [...] We guess it might interesting [to invest in this AI start-up]. In many cases, that guess is right” KA

This situation was found at six of the seven CVC units. However, five of these six CVC units could mitigate this impact thanks to moderators, as will be seen in the next section.

Three CVC programs also reported encountering ambiguity in implementing AI solutions, in learning how to exploit them. Here again, ambiguity did not stem directly from understanding AI technology,

but it had an impact in knowing how to use the technology. However, more data is required to confirm this finding, as the other programs did not report such challenges.

“Most of the case we know what the AI is and how to build the AI. The big difference for investor into the start-up side is how to implement or how to execute the AI so.... Of course, the deep knowledge such as “what is the algorithm of the AI, [how it] should apply to this program to solve it” ...so we know that from the investment perspective” SA

“Challenges are surprisingly not coming from the technological side. It is not a question of technology, it’s more a matter of process. [...] We have to reverse all the process” MA

“The challenge we have [...] is how this technology, tomorrow, can be used toward transforming customer service” RA

AI ambiguity as experienced by other open innovation structures

This situation is not unique to CVCs and could be found at the other open innovation structures, confirming the finding above. First, respondents corroborated they did not experience any challenges in dealing with AI. They were looking for general AI knowledge, and more specifically for already commercialized solutions. AI did not impact the knowledge transferability between their structure and their parent companies.

“To be honest, I don’t distinguish AI with any other technologies. AI is just one of the technologies” TA

“I think AI platform...I think [it] is a very hot topic... how to gather data in one place, how to analyse generally. But currently, the customer is focused on use cases [...] In manufacturing there are so many use cases in terms of producing, predictive maintenance, how to expand the manufacturing processes. [...] We are looking for use cases” HA

Takayama and Wallers, however, validated the impact of AI ambiguity on exploratory learning. Without a proper AI expertise, it became difficult to understand whether it was interesting to start collaborating with some AI start-ups.

“Actually I don’t know if [the solution provided by the AI] is good or not. It is really hard. They are many similar AI start-ups. That is why I have actually a problem. I basically select the start-up from our program. They maybe are better AI start-up somewhere, even in Japan.” TA

“Sometimes, some people say “we are using AI” but actually it is not AI. It is basically the same as excel, like an existing solution” TA

“Right now, [AI] is not advanced enough, there is always a mix between what is done by humans and what is done by AI. The question I ask myself from an AI business model point of view is are they doing AI they sell at a human price, or are they doing human tech they sell at an AI price” WA

Propositions

To summarize, although some AI technologies can be identified as ambiguous, ambiguity had only a limited effect on AI learning for the seven CVC units. Only general AI knowledge gets transferred between ventures, CVC and parent companies. This does not create any transferability challenges. Yet, ambiguity had an impact when it came to exploring AI solutions, as some CVC experience difficulties in properly understanding and evaluating start-ups solutions. Other also had difficulties in understanding how to exploit AI business model however more data is required to confirm this finding. Therefore the following propositions can be developed:

Proposition 8: AI ambiguity does not impact knowledge transferability in CVC relationships as only basic commercial knowledge gets transferred.

Proposition 9: AI ambiguity impacts the exploratory AI learning process of CVCs if parent companies or CVC units do not have access to an AI expertise.

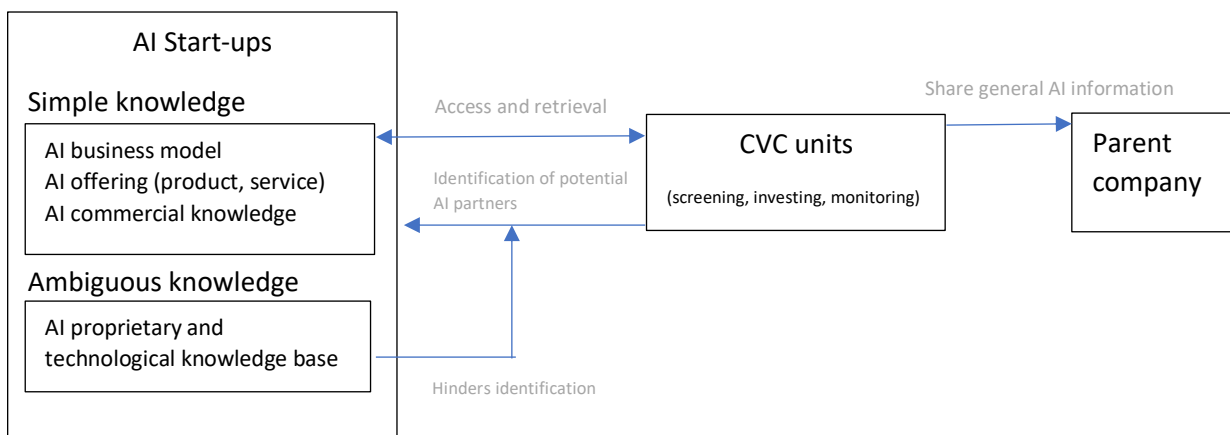


Figure 19 – Impact of AI ambiguity on CVC and AI learning relations

6.2.3 Moderators

The third sub-question of this research aimed to understand which moderators played a part in the relationship between CVC and AI learning processes. From the analysis, social ties, previous absorptive capacity and intra-organizational knowledge transfer capacity were significant moderators.

Social Ties

Social ties is the second factor of the inter-organizational dynamics moderators, which are a group of moderators looking into how relationships between organizations impact inter-organizational learning (Easterby-Smith, Lyles et Tsang, 2008). Social ties have been found to be a moderator of the exploratory learning process as well as in the impact of AI ambiguity.

Five CVC programs identified their external partners, such as VC funds or co-investors, as crucial partners in their exploratory activities. Those partners introduced promising AI ventures to the CVC units therefore oriented the investments choices of CVC, their sourcing opportunities, and the range of potential AI solutions discovery they made. While the absence of social ties did not put a stop to the CVCs' exploratory activities, their presence facilitated their investment choice and their gathering of AI information. Those external partners, and the tie strength CVC units sustained with them, were key in getting access to some popular start-ups or hardly sought-after AI information.

The following excerpt support the finding:

“The company [name of the company] has the business experience of managing several corporate venture fund [...] [It is a] very relationship based activity I guess. All the important information is shared under the table, shared behind bars table ...” A

“The activities of CVC or VC is the almost mainly based on network, people network. The network with investors or the networks with start-ups is critical for our operations. Good a co-investor experience, then they make another introduction to us because they trust us and we build a business with [the company] and they help us so it is a win win win situation.” KA

“Sourcing [of start-ups] is made in numerous ways, and we rely a lot on partners” MA

“[to] establish our credibility, [we were] working with U.S based VC. We [contacted external partners] to invest into the companies directly, and also [with] VC to build the relationship. [...] we rely on the VC transaction for a great deal. We emphasize the activities [that are]

more focused on building the connection with VC. They get the prospective opportunities of start-up to consider for investments.” SA

“The interest to invest in a fund like [name of partner] [...] is to have specialized people who will search what is going on and will tell you [all about it]” YA

The two other CVC units did not rely as much on social ties for their exploratory activities for the following reasons. The first may not have relied as much on social ties as it reviewed itself a larger number of start-ups per year compared to the other CVCs (>1000) hence could discover a wider range of solutions by itself. The second unit invested in fewer start-ups compared to the different unit and benefitted from its R&D AI expertise which may explain why it did not rely on social ties.

Social ties also played a part in mitigating the effects of AI ambiguity on CVC programs that did not benefit from an internal AI expertise. Two CVC units used their social ties to mitigate the effect AI ambiguity had on their exploratory activities. Investors partners of those CVCs were capable of providing them with useful information to the programs for them to invest wisely and in valuable AI investments. For one CVC, this partner was a VC fund, while the other relied on the expertise of large companies.

“Good point is [our VC partner] has and has hired tech talents, experts venture capitalist that have business background, education background of specific industries such as AI. I say [we do] not heavily but [we] still rel[y] on the expertise of [our VC partner] “A

“We have contacts and we have partnerships [...] We have contacts with other big companies such as ourselves [...] So we turn to our partners to see whether they have solutions. They say yes, we have like 10, we look at them and we make an internal start-up pitch” MA

Previous absorptive capacity

The firm absorptive capacity has been identified as having an impact on the ability for firms to learn from external partners as explained in previous sections (Lane, Koka et Pathak, 2006; Zahra et Hayton, 2008).

In AI CVC relationships, the parent company previous absorptive capacity was first a moderator capable of easing the ambiguity surrounding the identification of useful AI knowledge. CVCs relied

on their internal AI expertise (both at the CVC or parent company) or on external partners to measure the real value of the start-ups AI solutions, and whether they were indeed offering an AI solution:

“Of course, when we see AI in these companies, we discuss with AI specialist [at our parent company], so they do a technological due diligence so that it is cleared. But the first filtering is by us is getting difficult.” KA

“My coverage of the investment is AI [...] My experience, my background of researching AI, my major was computer science, I worked in IBM for software engineer, I am an engineer, I know how to build an AI, and how to implement the AI into the business. So this is why I can talk with the AI company, the CEO or the CTO side.” SA

“But using the technical skill that we have inside [our company], we can figure out which is a really good-start in technical wise or business-model wise. So we focus on those start-up” NA

“All the entrepreneurs will come to you, they will say yes “we have an amazing tech, a super advanced algorithm, we made an exceptional product at the MIT” and all....But if you don’t open the hood to check the engine, you can’t check if it’s true. So for us, we call technical experts that will check all this [...] [We will call] Data scientists that will look at the code, that will check...” WA

Previous absorptive capacity might also have an impact on the kind of AI learning performed through CVC. Two of the CVC units, Saitama and Nagano, both being under their R&D department and having an internal AI expertise reported focusing on AI investments that impacted directly their core businesses. On the other hand, the other CVC units focused more on case-by-case AI solutions, a situation that may be the result of a low AI expertise. However, additional data is required to confirm the exact impact of absorptive capacity.

“I know how to build an AI, and how to implement the AI into the business. [...] [We are] focused on new technologies or new business for [the] group for the future priorities of business” SA

“what we want to do is to collaborating with all of [our company] core technologies, sensing and control and adding new technologies or business models and we want to create the future of [the core businesses] [...] There is an AI researcher within the group [...] [the group has] developed many AI related new product.” NA

Intra-organizational knowledge transfer capacity

Finally, the capacity of a firm to diffuse knowledge it acquired inside its boundaries has an impact on organizational learning, specifically on transformative learning.

As said previously one CVC unit, Marseille, displayed such capacity by organizing meetings, fairs, presentation and other activities to diffuse knowledge. However, more data is required to confirm the impact of these many activities on the contribution of CVC to learning processes.

Across the CVC units, only the social network was found to have had an impact on CVC activities and organizational learning. The capacity of CVC employees to connect with their counterpart at their parent company was important in having AI solutions integrated at the right units in the parent company and in gaining time. The size of the CVC employees social network tended to be bigger for Japanese CVCs than French ones. It is frequent for Japanese employees to have long careers in a single company. Hence, many could develop a large network inside their company throughout the years. They could take advantage of this network when they encountered an interesting AI project. The following quotes highlight this situation:

“I have 25 years of experience in [the company]. [...] More than 15 years of experience in investments in Japanese and U.S Market” A

“The majority of the team is already [from our parent company]. They have their own background, etc. They are behaving like facilitators in developing.... For example, if I meet company A that is in AI, they may say well that company might fit this department which I know very well, something like that. We have about 10 people in the investments team, external investment background is three, including myself. The rest of the team if from [our parent company].” KA

Proposition

In light of what was described above, the following proposition was developed:

Proposition 10: Social ties, previous absorptive capacity and intra-organizational knowledge transfer capacity positively moderate the contribution of CVC activities to AI learning processes.

Chapter 7 Conclusion

The following part concludes this research paper. The first section provides this essay's results summary, and a revised conceptual framework model. Then, the second section displays this research limits while the third presents its contributions. Finally, the fourth section provides avenues for future research.

7.1 Results summary

This research focused on the relationship between CVC and organizational learning. It was driven by the renewed interest in recent years in CVC, a corporate investment mode, and AI, a promising set of technologies. CVC enables knowledge transfer between organizations (Dushnitsky et Lenox, 2005b). It can theoretically lead to knowledge creation, knowledge retention or further knowledge transfer at its parent company. In other words, CVC activities might be used by companies to gain experience and learn new pieces of knowledge. The aim of this paper was to determine how CVC could contribute to its parent company learning effort. This essay used AI, an ambiguous and desirable set of technologies, as a research setting to analyze this relationship.

This research effort was motivated by the presence of gaps, identified by scholars, in the CVC literature. Few studies have thoroughly analyzed the relationship between CVC and organizational learning. Consequently, there was no reliable evidence showing that CVC activities led to organizational learning for a company, or what the learning benefits of CVC could be (Keil *et al.*, 2008; Keil, Zahra et Maula, 2016: 260; Wadhwa et Kotha, 2006). There was a gap in understanding how, what and to which extent companies learn through CVC and how it affected their internal activities (Dushnitsky et Lenox, 2005b; Keil, Zahra et Maula, 2016; Volberda, Foss et Lyles, 2010). Besides, the effect of knowledge characteristics, such as ambiguity, on CVC relationships also was largely ignored in the literature (Phelps, Heidl et Wadhwa, 2012). Therefore, this research aimed to answer the following question: **How do CVC activities contribute to a company's AI learning effort?**

This paper developed three sub-questions from the main research question. This first sub-question aimed to clarify the impact of CVC on AI learning processes. To measure this impact, this research analyzed the organizational learning subprocesses (knowledge transfer, creation and retention)

(Argote, 2013) to understand how parent companies learned AI. It also reviewed the absorptive capacity learning process (exploration, transformation and exploitation) (Lane, Koka et Pathak, 2006) to understand what parent companies learned. The second sub-question looked into the ambiguity of AI, to see whether it impacted the parent companies learning effort of AI. Finally, the third sub-question examined the moderators in the relationship between CVC and AI learning.

To answer the research question, this study has analyzed 10 companies involved in AI activities in France and Japan, including 7 CVC units. This research setting was deemed appropriate as both these countries are currently developing their AI capabilities (Ministère de l'économie et des finances et Atawao Consulting, 2019; Scappaticci, 2018).

The data analysis helped develop 10 propositions emerging from the research question.

Three propositions first fill research gaps in explaining how AI learning occurred at parent companies using CVC. It was found that while CVC activities permit the transfer of AI knowledge from the ventures to the parent companies, the knowledge transferred is a basic and general commercial AI knowledge (proposition 1). No technological AI knowledge gets transferred in CVC relationships. In these conditions, AI learning taking place at the parent companies was very limited. The data showed CVC activities did not lead to any AI knowledge retention (proposition 4) nor did it impact directly AI knowledge creation (proposition 7).

Despite the limited opportunity for AI learning, four propositions explain what learnings were still achieved by looking into absorptive capacity learning processes. CVC activities first contribute to enriching their parent company AI exploratory learning process by widening the range of AI solutions it could explore. CVC activities offer an opportunity to discover AI solutions regular units at their parent company could not have the resources to explore (proposition 2). CVC programs also improved their parent company AI transformative learning process. Pushed by their strategic and financial objectives, CVC units trigger the introduction of AI at their parent company (proposition 3) and promote learning in knowing when and where to use AI solutions (proposition 5). Finally, through CVCs parent companies gain experience in experimenting with AI and outsourcing their AI needs (commercial and technological), thus accelerating their commercial and innovative outcomes (proposition 6).

Two propositions also look into the impact of AI characteristics on the relationship between CVC and AI learning. The analysis shows AI ambiguity does not have a major impact on CVC activities (proposition 8). This situation can be explained as AI ambiguity stems mainly from its technological intricacy. Since technological knowledge did not get transferred following CVC investments, it mitigated the impact of ambiguity on learning processes. AI ambiguity only manifests itself during exploratory learning process if units do not possess prior AI expertise (proposition 9).

Finally, proposition 10 shows that intra-organizational transfer capacity, prior AI absorptive capacity and social ties moderate the relationship between CVC activities and AI learning.

Hence, CVC programs contribute to the AI learning effort of their company despite the limited learning effects they provide. These units are an open innovation tool that must be used in parallel to traditional R&D internal activities. While this essay focused on AI knowledge, it is relevant to note that CVC units may produce the same kind of learning for other technologies. However CVC were an interesting medium for the companies interviewed, as it helped by-pass the apparent complexity of AI and accelerated the integration of AI solutions.

Table 17 displays the revised research propositions following the data analysis, while figure 20 shows this research conceptual framework model.

Table 17 - Research propositions

Proposition number	Detail
1	Only commercial AI knowledge gets transferred between partners in an AI CVC relationship.
2	CVC AI investments increase the range of AI commercial knowledge explored by a company, thus accelerating its understanding of AI benefits and business models.
3	CVC AI investments triggers the integration and assimilation of AI solutions at the parent company
4	CVC AI investments do not lead to any AI knowledge retention at the parent company, as commercial AI knowledge seldom gets reused.
5	Investing in AI start-ups through CVC guide the parent company in its technological and strategic decision-making, helping it decide when and where AI knowledge should be used.
6	Investing in AI start-ups through CVC can help a firm gain experience in exploiting AI solutions through experimentation and sub-contracting.
7	Investing in AI start-ups through CVC does not directly impact the ability of a firm to create AI knowledge.
8	AI ambiguity does not impact knowledge transferability in CVC relationships as only basic knowledge gets transferred
9	AI ambiguity impacts the exploratory AI learning process of CVCs if parent companies or CVC units do not have access to an AI expertise.
10	Social ties, previous absorptive capacity and intra-organizational knowledge transfer capacity positively moderate the contribution of CVC activities to AI learning processes.

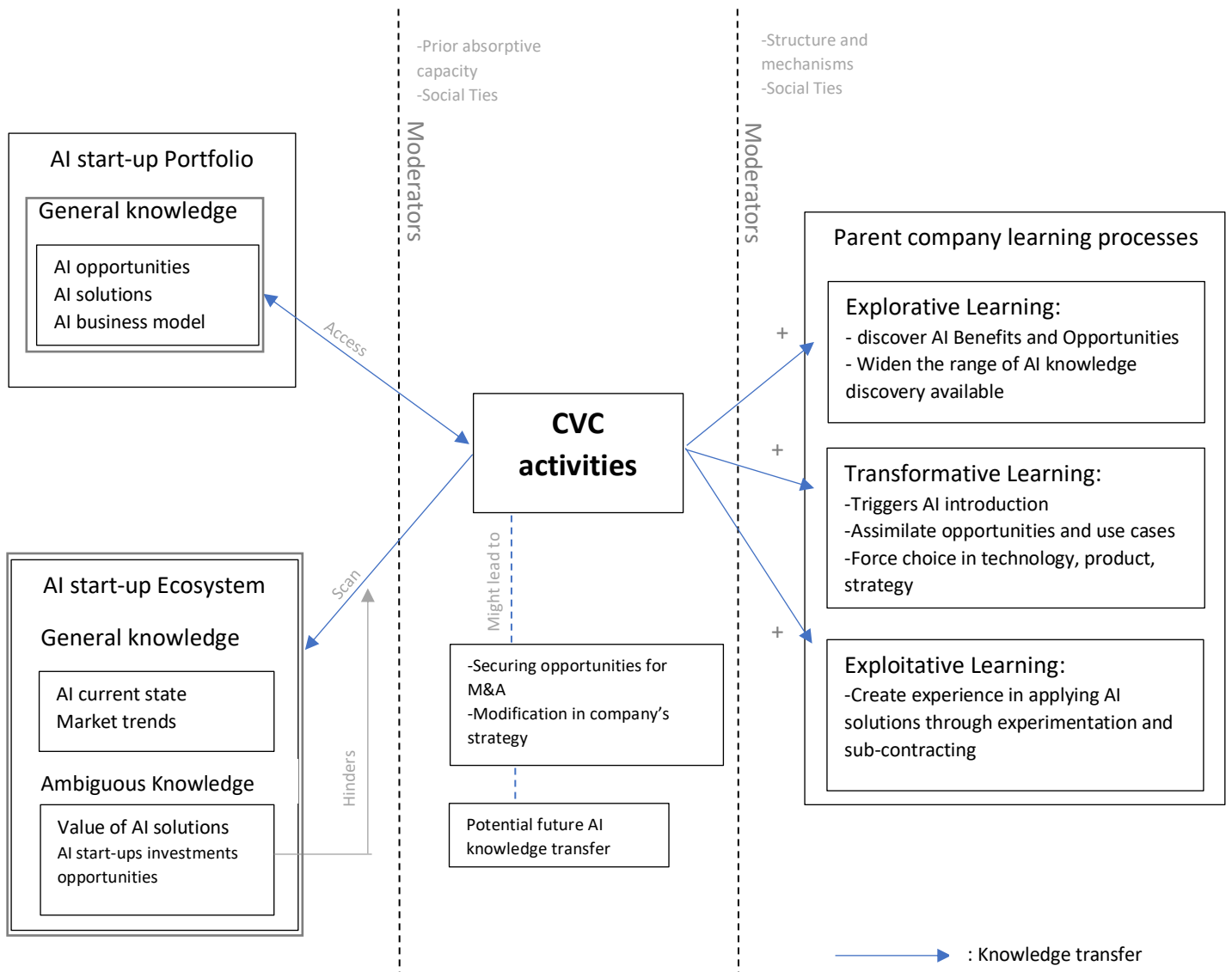


Figure 20 - Conceptual framework model

7.2 Research limits

This research contains several limits that need to be addressed.

The first limit deals with the data collection process. Unfortunately, they were only a limited number of respondents in this research. This research would have benefited from getting additional CVC and business units' managers point of view. This research findings would also have been improved if multiple interviews had been conducted at the same company. Sadly, despite several attempts, it proved impossible to organize those interviews. Most case studies consisted in a single interview. However, the majority of participants in this research held important positions at their companies. They had a keen understanding of their organizations. This was thought to have lessened the limited pool of respondents' impact.

Another limit concerns the generalization of findings. Per its nature, AI was characterized as an ambiguous knowledge. The analysis found AI ambiguity did not have a significant impact on knowledge transfer. However, it is not possible to confirm with certainty that all ambiguous pieces of knowledge will impact knowledge transfer in the same way as AI. Other ambiguous pieces of knowledge may differ in complexity, tacitness or specificity. In general, generalizing findings from qualitative data can prove difficult (Cooper et Schindler, 2011: 160-183). Participants in this research were large companies which evolved in the French and Japanese business environments. It is thus difficult to generalize findings for smaller companies or international companies outside the French and Japanese business context.

From a methodological point of view, this research measured learning in a specific way, which could prove to be another limit. While measuring learning is complex in nature (Argote, 2013), there may have better ways to measure AI learning at parent companies more precisely. On one hand, this research relied on qualitative data to observe change in the learning processes of receiving companies. There could have been bias in the participants answers despite efforts to ensure this research validity. For example, while it is unlikely, respondents may have avoided talking about knowledge misappropriation cases to protect their units reputation. On the other hand, while the research framework helped in understanding CVC contribution to AI learning, it could not contrast how this contribution differed from other sources of AI learning at parent companies.

7.3 Research contributions

This research has direct implications for managers looking to acquire external knowledge sources or establish open innovation strategies at their companies. It provides them with relevant pieces of information regarding the benefits corporate venture capital can bring on organizational learning processes. First, this paper explains in detail how companies can use corporate venture capital as an investment mode. It details CVC objectives, benefits and management. On the other hand, this research also explains what is meant by organizational learning, how organizations learn through knowledge transfer, knowledge creation and knowledge retention. It studies the link between those two concepts through a concrete example: the acquisition of AI knowledge, a set of technologies attracting considerable attention in recent years.

CVC could be used as a strategic tool for parent companies. It can accelerate companies' innovation processes and produce commercial outputs by relying on start-ups partners. CVC activities increase the range of innovative solutions parent companies can explore, even intricate pieces of knowledge, without having to spend additional R&D efforts. Through CVCs, respondents' parent companies could refine their operations by integrating AI solutions they would not have had the time nor the resources to develop. In general, by introducing their portfolio to their parent companies, CVC activities force business units and top management to reflect on their knowledge needs, and on ways to improve their operations. Thanks to CVC activities, the top management may gather sufficient information to predict future organizational needs, influencing the corporate strategy. Participants in this research have also reported having been able to discover new AI solutions. They have experimented with them and applied them. Using CVCs, parent companies gain the experience of translating AI technological opportunities into commercial outputs with limited risks and expenses.

Yet, CVC activities do not substitute any R&D efforts for a company. Rather, it acts as a complement. It can be used by managers to discover innovative solutions that are either not directly related to a company core operation or that could potentially have an impact on the company's operations. CVC activities are not useful to learn about the content of promising technologies or pieces of knowledge. Parent companies in this research did not learn anything new regarding AI technologies. However,

it was a way for respondents to gather AI market intelligence and explore AI knowledge solutions that could prove to be interesting for their companies' future.

This research also makes theoretical contributions. First, the literature review allowed for the discovery of several gaps in the CVC literature. Those gaps made it difficult to understand precisely the extent to which CVC programs impacted their parent companies' learning processes. Few studies had analyzed how, what and to which extent companies learned in this investment mode (Dushnitsky et Lenox, 2005b; Keil, Zahra et Maula, 2016: 282). When they did, these studies focused more on learning outcomes rather than on learning processes themselves (Keil, Zahra et Maula, 2016: 282). Scholars also did not study the influence of knowledge characteristics on CVC knowledge transfer, nor did have they clarified the type of knowledge being transferred (Phelps, Heidl et Wadhwa, 2012; Volberda, Foss et Lyles, 2010).

This research answered those gaps using an original conceptual framework. Previous research focused on the learning outcomes of CVC activities by measuring patent activities or product release. This paper studies learning processes in detail by taking advantage of the recursive relationship between learning and absorptive capacity (Lane, Koka et Pathak, 2006) and by focusing on organizational learning subprocesses. This essay shed new findings on the relationship between CVC and organizational learning by studying the impact of CVC on those different learning processes. From CVC activities, an inter-organizational transfer took place which in turn had a positive impact on the exploratory and transformative learning processes of parent companies. In a lesser way, CVC impacted the exploitative learning of parent companies. In AI CVCs, the knowledge being transferred is only general and commercial, which does not lead to any knowledge retention. CVC does not directly impact knowledge creation, even though it could potentially lead to M&A or modification of its company's strategy.

Using previous work from Simonin (1999) and Szulanski (1996), this research also studied the impact of ambiguity on CVC knowledge transfer, an antecedent to organizational learning. It found ambiguity to have a limited impact, as pieces of knowledge transferred in CVC relationships are primarily explicit and general.

7.4 Futures avenues of research

This research has thrown up many questions in need of further investigations.

Further research might explore the differences existing between the various CVC structures and their impact on organizational learning. In this research, “independent” CVCs and “R&D” CVCs seemed to cause diverse impact on the AI absorptive capacity of their companies. Being attached to their R&D departments, “R&D” CVCs were more “future-oriented”. The intent to learn seemed to differ: “R&D” CVCs diffused their AI knowledge to multiple levels of their organization from top management to business units. “Independent” CVCs, however, seemed more eager to link their ventures to business units directly. “R&D” CVCs seemed to have had a bigger impact on their company strategy compared to “independent” CVC structure. Yet, more research is required to confirm this finding.

Another avenue for research would be to study whether parent companies that have acquired an AI CVC portfolio start-up have experienced knowledge creation following the integration of the venture. This would allow to confirm or infirm whether CVC could indirectly participate to knowledge creation.

This research adopted a corporate perspective in examining the relationship between CVC and organizational learning. However, future research might investigate the link between CVC and organizational learning from an entrepreneurial perspective. How does CVC contribute to the AI innovation effort of their start-up’s portfolio? Ventures could benefit from the technical and business support from their corporate partners. Hence, it would be interesting to study whether the relationships help in enhancing the ventures R&D effort.

Finally, more research is required to confirm the impact of ambiguity on knowledge transfer in CVC relationships. It would be relevant to analyze how other ambiguous pieces of knowledge influence CVC in other industries, such as the medical industry.

Appendix

Appendix 1 History of AI

The work of Alan Turing, on computing and logic, could be considered the origin of AI. However as a research field AI was only launched during summer 1956 in Dartmouth College, at the initiative of John McCarthy and Marvin Minsky (Prade, 2018). In the 1950s and 1960s, AI research efforts were based on creating programs that could mimic human problem-solving ability by applying logic to pre-defined objects and actions (Greenwald, 2018). Those systems were called expert systems, functioning in an “if...then” pattern (Burgess, 2018). These systems often failed due to the numerous possibilities in mapping entities or instructions (Greenwald, 2018). As such, the initial interest that AI provided diminished overtime, mainly because of limited computing power (Scappaticci, 2018).

Despite this, the 1970s saw the advent of the first knowledge-based systems. By basing systems on small amounts of knowledge, researchers could enable more intelligent decision-making program (Buchanan, 2005). Once again, it was limited in scope, as accumulating knowledge proved difficult at that time. Hence, AI experienced its first “winter” between 1974 and 1980 (Burgess, 2018). In practice, some governments including, but not limited to, the United States and the United Kingdom withdrew their funding in AI research as several projects results were considered unsatisfying. Notwithstanding this freezing in research sponsoring, several AI expert systems were invented in the 1980s then put in place in specific fields (chemistry, medicine) following logical “if...then” rules (Prade, 2018). Yet, expert systems proved difficult to run and were still expensive (Burgess, 2018). The second AI winter occurred between 1987 and 1993 as a result (Burgess, 2018). An illustration of this collapse could be Japan’s “Fifth-generation computer”, an ambitious 850 million USD AI program. Launched in 1981 with the intent of creating the first intelligent computer (Scappaticci, 2018), the project was cancelled in 1991 after it had failed to meet its objectives (Burgess, 2018).

In the 1990s AI met one of its first major successes. IBM’s chess program “Deep Blue” became in 1997 the first machine to win the chess world championship. The period also saw the arrival of the World Wide Web (Internet) which rapidly changed the way humans share information and knowledge. This phenomenon would later be called the “emergence of a new continent” (Niita,

2017) as the amount of information becoming accessible through computer devices skyrocketed. Internet helped reshape AI, as it suddenly allowed for large amounts of data to be accumulated and shared, something costly and nearly impossible to perform a few decades ago (Skilton et Hovsepian, 2018).

Essentially, AI algorithms did not change since the past decades. But to be able to perform well, algorithms need a large amount of data as input. Burgess (2018) highlights that training an AI system requires millions of examples. Around 30% of any given data set is commonly used for training and testing the AI, according to the author. The rise of data accumulation (otherwise known as Big data), linked to a huge decrease in storage cost (from 437,500\$ / GB in 1980 to 2 cents in 2016) and increased computer processing power, helped improve AI systems greatly (Burgess, 2018). Today, with other technologies such as cloud computing, companies can even manage big data without having to pay for their data infrastructure and associated risk (Burgess, 2018). For the author, many companies currently have large data sets that can be accessed instantly to feed AI technologies. In the 2010s a new breakthrough came, disrupting AI. The invention of “deep neural networks”, devices mirroring human neural networks, improved machine learning even further. A third boom began for AI technology, with governments and companies investing to develop and exploit its capabilities (Scappaticci, 2018).

Appendix 2 E-mail Model

-----株式会社

ご担当者様

初めまして、一橋大学大学院経営管理研究科研究生の Guillaume Charron (ギヨム・シャロン)と申します。

突然のメール、大変申し訳ありません。

私は修士課程において「企業間学習における知識移転のプロセス」を研究しております。特に、企業のコーポレート・ベンチャー・キャピタル (CVC) 活動において、投資側の事業会社とスタートアップの間でどのような知識移転が行われているのかや、知識の特徴が学習成果にどのような影響を及ぼすかについて研究したいと思っております。

具体的に私の研究では人工知能 (AI) に関する知識移転に注目をしており、人工知能関連のベンチャー企業に投資をしている日本企業に焦点を当てた調査を行いたいと思っております。知識移転の実態を把握するために、CVC 担当のマネジャーや AI 関連の研究部門のマネジャーの方にお話を伺いたいと思っております。

もしお時間が頂けるようでしたら、御社にて直接担当者の方にお会いしてインタビューをさせて頂けないでしょうか。インタビューは約一時間を予定しております。インタビューは私の研究論文にとって非常に有益なものであり、また論文完成後は、研究結果を是非共有させて頂きたいと考えております。もし可能でしたらインタビューは英語で行いたく存じます。ただし、ご希望があれば日本語でも可能です。

収集されたすべてのデータは厳重に匿名で管理いたします。また、インタビューの受諾及びご回答は任意であり、全て回答者の同意のもとで行われます。

ご多忙のところ、大変恐縮ではございますが、ご検討のほど、どうぞよろしくお願いいたします。

Merci beaucoup!

何卒よろしくお願い申し上げます。

ギヨム シャロン

Dear Madam, Dear Sir,

My name is Guillaume Charron, I am a master student at Hitotsubashi University and HEC Montréal in business administration. I am reaching to you today as I am currently conducting an academic research as part of my master program. In this research, I try to analyze the process of knowledge transfer in corporate venture capital relationships. Specifically, I study how Artificial Intelligence ("AI") gets transferred in these investment relationships.

As such, I want to study Japanese corporations that have conducted or are conducting CVC investments in AI start-ups. Therefore, I am looking for managers of CVC units, or managers at parent companies' research departments, willing to share their experience regarding this subject. As I saw that [company's name] was involved in this type of activity, I was wondering whether it would be possible to meet with you for an interview. The latter should last approximately one hour.

Your help would be precious for the success of my research. Once it is finished, I could share my research results with you. All data collected will remain strictly confidential and anonymous, and limited to this research's use. Your participation is left to your discretion and subject to your consent.

I remain at your disposal to answer any question you may have.

Thank you very much in advance for your answer, your time and your help.

Best regards,

Guillaume Charron

Madame, Monsieur,

Je m'appelle Guillaume Charron et je suis présentement étudiant en master à HEC Montréal (Canada) ainsi qu'à l'université Hitotsubashi (Japon). Je me permets de vous contacter aujourd'hui, car je suis actuellement en train de mener une recherche académique dans le cadre de mon programme de M.Sc.

Dans cette recherche, j'essaie de comprendre le fonctionnement des processus de transfert de savoirs des structures de corporate venture capital (« CVC »). Autrement dit, je cherche à saisir la manière dont les entreprises « apprennent », ou trouvent des synergies, grâce à leurs investissements CVC. En particulier, je m'intéresse à savoir de quelle façon les connaissances liées aux technologies d'intelligence artificielle (« IA ») se transmettent le long de telles structures d'investissement. Mon étude se veut internationale puisque j'étudie tant des CVC Français que Japonais.

Je suis à la recherche de gestionnaires d'entreprises ou d'unités de CVC françaises ayant récemment investi dans des startups reliées à l'IA et qui souhaiteraient partager leur expérience à ce sujet. Ayant remarqué que [Nom de la compagnie] a effectué de tels investissements, auriez-vous un peu de temps à m'accorder pour une entrevue ? Cette dernière durerait moins d'une heure.

Votre aide serait un appui considérable pour ma recherche et je vous en serais très reconnaissant. Une fois finie, je pourrai bien évidemment partager les résultats de cette dernière avec vous. Votre participation est entièrement volontaire. Veuillez également noter que les données récoltées pour cette recherche sont strictement confidentielles et ne seront utilisées que dans ce cadre académique.

Je vous remercie par avance de votre réponse ainsi que de votre aide, et vous souhaite une agréable journée.

Cordialement,

Guillaume Charron

Appendix 3 Interview Guide

First of all, I want to thank you for agreeing to participate in this research. As a reminder, I am currently conducting a research regarding knowledge transfer between organizations. It specifically concerns AI knowledge transfer in CVC relations. This interview's goal is really to understand how your company handles its CVC investments in AI ventures. To begin, I was wondering if it was possible for you to introduce yourself.

Theme	Sub-theme	Question / Probe	Purpose
Background information / Opening questions	Interviewee Information	1) Could you introduce yourself? <ul style="list-style-type: none"> a. Position in the company, key responsibilities b. How long have you been in the CVC/ parent company? c. Start-up / entrepreneurial experience d. Experience in AI 	General information of the interviewee
	Unit description	2) Could you introduce your unit? <ul style="list-style-type: none"> a. Mission & objectives b. Structure c. Unit experience in CVC investments / in AI investments 	Understanding the structure and mechanisms in place in the unit
CVC / unit process	CVC management	3) Can you explain how you manage your investments from their start until their end? <ul style="list-style-type: none"> a. Selection of ventures b. Additional financing round c. Exit strategy (how is the decision taken)? 4) Can you explain how you interact with the AI ventures, from the start of the investment process?	Understand the steps taken during the CVC process – Understand the process of CVC knowledge transfer

		<ul style="list-style-type: none"> a. Contact (frequency, how?) b. Monitoring (how?) c. Collaboration? <p>5) How do you interact with your parent company during this process?</p> <ul style="list-style-type: none"> a. Contacts (department?) frequency of contact b. Independence from parent in decision-making? c. Reports (KPI, etc.) d. What kind of information / knowledge is shared? e. How is it shared? (e-mail, face-to-face, etc.) f. If no contact, could you explain why? 	
	Purpose of investing in AI	<p>6) Why did you invest in AI?</p> <ul style="list-style-type: none"> a. How important was it to work with AI start-up for your company? b. Parent company involvement in investing decision? c. What is the link between ventures technology and own AI strategy / other business strategy? d. How was the R&D department implied? 	<p>Understanding what kind of problem the company is trying to solve with AI (its goal), the motive behind CVC investment; Understand whether the company uses external knowledge for problem-solving</p>
AI Learning processes	AI transferability	<p>7) How do you think AI compare to other technologies?</p> <ul style="list-style-type: none"> a. How do your AI investments compare to your other CVC technology investments? <p>8) What were the challenges you faced in investing and working with AI ventures?</p> <ul style="list-style-type: none"> a. How do these challenges compare to your other technological investments? b. How did you deal with them? What helped overcome these challenges? c. If no challenges, did something help in erasing these difficulties? 	<p>Grasp the perception of participants on AI, identify how AI ambiguity is defined by interviewee</p>
	Knowledge transfer process / Learning outcomes	<p>9) What do you think has changed at your company since you started investing in AI?</p> <ul style="list-style-type: none"> a. How has your unit changed? b. How have your R&D projects been impacted? c. How have your parent company operations been impacted? <p>10) How has your AI knowledge changed following your investments?</p> <ul style="list-style-type: none"> a. If no learning, why do you think that is? b. How has your parent company AI knowledge changed? 	<p>Understand AI knowledge transfer process</p> <p>Understand the change observed by interviewee in their AI expertise either at their unit or at their parent company level</p>

		<ul style="list-style-type: none"> c. How does this AI learning compare to learnings made in different CVC investments? <p>11) What would you say were the main outcomes of investing with AI ventures?</p> <ul style="list-style-type: none"> a. What have you been able to discover? b. Joint projects c. R&D outcomes d. Commercial outcomes e. How does this learning compare to learnings made in different CVC investments? <p>12) How do your CVC activities complement your parent company AI innovation effort?</p>	
Moderators	Enablers	<p>13) What do you think are the elements that helped in investing in and working with AI ventures?</p> <ul style="list-style-type: none"> a. What elements help find relevant AI partners? b. What elements help to gain their trust? c. How eager were the AI ventures to support and help you? <p>14) What elements linking your AI portfolio to your parent company?</p> <ul style="list-style-type: none"> a. Structure and transfer mechanisms with the CVC b. Social ties to the CVC unit members c. Own expertise regarding AI d. In what ways do these elements differ from other non-AI related CVC knowledge transfer? 	Identify the moderators in the relationships between knowledge ambiguity, CVC and learning
Concluding question		<p>15) What are the advantages of investing in start-up than accelerate or incubate it?</p> <p>16) Ideally, how should AI be used in your company?</p> <p>We've reached the end of this interview. Thank you again for your participation and help in this research project. Is there anything you would like to add?</p>	

Some questions were modified for interviews with non-CVC units. For example, question 3) was modified to “Can you explain how you manage your acceleration program from its start until its end?” for the interview with the acceleration program manager.

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