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POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

The adoption of advanced technologies in Canada and their impact on innovation propensity

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Thèse en vue de l'obtention du diplôme de *Philosophiae Doctor*

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The adoption of advanced technologies in Canada and their impact on innovation propensity

Présentée par: **Georges HAGE**

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a été dûment acceptée par le jury d'examen constitué de :

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Pierre HADAYA , membre

Elicia MAINE, membre externe

DEDICATION

To Gisèle, for being a model of inspiration and perseverance…

À Gisèle, pour avoir été un modèle d'inspiration et de persévérance

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This document summarizes many years of doctoral research and key moments of my life, whether it is moments of strength or weakness, happiness or sadness as well as anything else that can be felt on the spectrum of emotions. As consequence, this thesis has contributed to define the person I am today, both personally and professionally. This PhD did not only play a role in my academic experience but helped me develop many other skills such as political acumen, a better capacity to analyze data and improved my organization and project management dimensions. More than anything else, it taught me about the importance of patience and that life is not a sprint but rather a marathon.

While these words are only describing the academic knowledge that I gained through the years, it should be noted that hiding between the lines is the priceless experience that was developed to help me take better decisions in my life. Whether it is through founding a company, teaching, helping and or coaching others, the invaluable experience gained transcends these words.

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I would like to thank my parents, my brother and my sister who have been the most patient family one could ever hope for. Through ups and downs, you always believed in my capacity to fully conduct this research. You always wanted me to surpass myself and I know that you will always be there to inspire me and show me the right path through determination and success.

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RÉSUMÉ

Bien que de nombreuses études aient exploré le rôle de l'adoption de la technologie sur l'innovation et le rendement des entreprises, toutes se sont concentrées sur quelques technologies et sur une catégorie en particulier. Les avantages de leur adoption ont été démontrés par de nombreux chercheurs et comprennent notamment l'augmentation de la productivité, une meilleure qualité des produits, la réduction des coûts, une meilleure adaptation aux besoins des clients, etc. Dans cette thèse, nous examinons une liste exhaustive de technologies appartenant à 4 catégories principales: la chaîne d'approvisionnement, l'intelligence d'affaires ainsi que la fabrication de pointe, qui est normalement divisée en deux sous-catégories, la conception et la fabrication.

Notre recherche explore ces technologies sous différents angles pour comprendre leur effet sur la propension à innover. Nous utilisons trois approches différentes pour analyser l'impact de ces technologies. Tout d'abord, nous examinons le nombre de technologies adoptées combinées à des pratiques d'innovation ouverte qui auraient un effet sur la propension à innover. Pour estimer ces facteurs, nous utilisons une simple régression logistique. Parce que nous nous intéressons aux obstacles qui empêchent l'adoption, nous utilisons un modèle variable instrumental où nous considérons l'adoption des technologies comme endogènes. Les variables qui peuvent influer sur l'adoption de la technologie comprennent : les dépenses en immobilisations (CAPEX), les mesures de nombre adoptées pour contrer les obstacles ainsi que le recrutement d'employés liés à l'adoption de la technologie. La deuxième approche que nous utilisons est une analyse de panier de marché (MBA) utilisant l'algorithme *apriori* contenu dans une librairie R. Un MBA nous permet de trouver des complémentarités entre les technologies car les résultats montrent les faisceaux de technologies qui sont les plus populaires parmi les entreprises. En utilisant chaque famille de technologies, nous pouvons trouver ceux qui sont achetés ensemble le plus souvent. Enfin, en utilisant une autre librairie R (*cspade*), nous utilisons une autre approche qui ajoute une notion séquentielle à l'adoption. Non seulement nous pouvons trouver quelles technologies sont adoptées dans les mêmes faisceaux, mais nous pouvons également comprendre lesquelles sont adoptées en premier. L'enquête que nous utilisons fournit des informations sur le moment où une technologie a été adoptée (pour 3 ans, moins de 3 ans ou prévue dans les 3 prochaines années). Ces 3 timestamps sont essentiels pour comprendre que les entreprises adoptent les bons outils menant à des technologies émergentes telles que l'IdO et l'IA dans un proche avenir.

Nos résultats montrent que le nombre de technologies adoptées a un impact significatif et positif sur la propension à innover, ce qui est vrai pour toutes les familles de technologies. En outre, les pratiques d'innovation ouverte telles que les alliances stratégiques et la collaboration avec les fournisseurs ont un impact positif sur la propension à innover, ce qui est similaire à ce qui a été trouvé dans des recherches antérieures. Le nombre de technologies adoptées a une incidence sur le nombre de mesures d'atténuation adoptées, un CAPEX plus élevé et sur le recrutement de nouveaux employés relatifs à l'adoption. Les trois variables ont un effet significatif et positif. Nous trouvons également des ensembles de technologies qui sont compatibles avec ce que nous avions prédit sur la base de notre examen technique exhaustif. Par exemple, des outils comme WMS (Warehouse Management System), Demand Forecasting (DF) et Customer Relation Management (CRM) constituent le faisceau le plus populaire lié aux technologies de la chaîne d'approvisionnement. Ce résultat a été prédit parce qu'il y a trois outils qui sont essentiels au processus de la chaîne d'approvisionnement qui permettent aux entreprises d'être efficaces lorsqu'elles prévoient la demande et gèrent les besoins des clients. Dans la catégorie Business Intelligence (BI), le groupe le plus populaire comprenait Software-as-a-service (SaaS) et Infrastructure-as-a-service (IaaS) avec plus de 27% des entreprises qui les adoptent. SaaS est particulièrement important pour les petites entreprises qui ne veulent pas construire une infrastructure pour gérer leurs besoins en technologies de l'information (TI). Dans les technologies de fabrication de pointe, ERP et MRPI ont été les groupes les plus populaires avec un taux d'adoption de 15%, tandis que les robots et le contrôle numérique informatique (CNC) ont été adoptés par 7% des entreprises. Malgré des taux d'adoption plus faibles dans le domaine de la fabrication, lorsque nous avons examiné les entreprises qui avaient l'intention d'adopter, nous avons remarqué que les technologies d'impression 3D étaient parmi les plus populaires. Nous voyons un résultat similaire lorsque nous examinons les technologies BI avec un logiciel de données massives (BDS), qui est une condition préalable pour rendre la mise en œuvre de l'IA possible à l'avenir. Bien qu'en 2014 l'adoption du BDS ait été faible, nous constatons une augmentation constante lorsque nous analysons les entreprises qui prévoient l'adopter.

En ajoutant une composante temporelle aux règles d'associations, il y avait entre 12% et 14% qu'une entreprise adopte un logiciel de données massives dans un temps futur. En combinant BDS et RTM en une seule technologie, le taux d'adoption d'une de ces deux technologies augmente à

40%. Une histoire similaire s'est dressée pour l'utilisation des imprimantes 3D. Lorsqu'elles sont considérées individuellement, le taux d'adoption futur est autour de 16%. Lorsqu'on considère au moins une des trois types d'imprimantes (3DP, 3DM ou 3DO), le taux d'adoption augmente à 33%, suggérant qu'une compagnie sur trois à l'intention d'adopter cette technologie dans le futur.

Notre étude a des implications théoriques et pratiques. Premièrement, nous avons démontré que l'adoption de technologies de pointe peut avoir un effet endogène sur la propension à innover. Cet effet s'explique par le nombre de mesures d'atténuation adoptées pour contrer les obstacles à l'adoption, le CAPEX pour n'en nommer que quelques-uns. Nous avons également trouvé des faisceaux populaires de technologies qui sont adoptées ensemble. D'un point de vue théorique, c'est la première fois qu'une analyse du panier de marché (MBA) est utilisée pour comprendre le comportement des entreprises adoptant des technologies de pointe qui jouent un rôle dans l'amélioration des performances en matière d'innovation. D'un point de vue pratique, nous avons constaté que si les entreprises préfèrent acheter des technologies « à la carte », il existe encore des modèles émergents qui pourraient se traduire par des pratiques exemplaires pour les entreprises à la recherche de technologies qui peuvent le mieux servir leur cœur de métier.

ABSTRACT

While many studies have explored technology the role of technology adoption on innovation and firm performance, there were all focussed on a few technologies and on one category in particular. The benefits of adopting them have been demonstrated by many scholars and include productivity increase, better product quality, cost reduction, better adaptation to customers' needs, etc. This thesis explores an exhaustive list of technologies from four main categories: supply chain, business intelligence and analytics as well as advanced manufacturing, which is normally divided into two subcategories, design and fabrication.

This research explores these technologies from various angles to understand their effect on the propensity to innovate. Three different approaches are used to analyze the impact of these technologies. First, the number of technologies adopted combined with open innovation practices that are thought to have an effect on the propensity to innovate are explored. To estimate these factors, a simple logistic regression is used. Because there is an interest in the obstacles that prevent adoption, an instrumental variable model is used, where the adoption of technologies is considered as endogenous. Variables that can affect technology adoption include capital expenditures (CAPEX), the number measures adopted to counter obstacles as well as the recruitment of employees pertaining to technology adoption. The second approach used is a market basket (MBA) analysis using the *apriori* library in R. A MBA allows to find complementarities between technologies because results show the bundles of technologies that are the most popular amongst firms. Using each family of technologies, it is possible to find the ones that are purchased together most often. Finally, using an additional R library (*cspade*), another approach that adds a sequential notion to the adoption is adopted. Not only it becomes possible to find which technologies are adopted within the same bundles, but understanding which ones are adopted first can also be studied. The survey provides information on when a technology has been adopted (for three years, less than three years or planned in the next three years). These three timestamps are crucial to understand companies are adopting the right tools leading to emerging technologies such as IoT and AI in the near future.

The results show that the number of adopted technologies has a significant and positive impact on the propensity to innovate and this is true across all families of technologies. Furthermore, open

innovation practices such as strategic alliances and collaboration with suppliers have positive impact on the propensity to innovate, which is what is similar to what was found in previous research. The number of adopted technologies is impacted by the number of mitigating measures adopted, a higher CAPEX and by the recruitment of new employees pertaining to the adoption. All three variables have a significant and positive effect. It should be noted that bundles of technologies that are consistent with what was predicted based on the exhaustive technical review were also found. For instance, tools like Warehouse Management System (WMS), Demand Forecasting (DF) and Customer Relation Management (CRM) form the most popular bundle related to supply chain technologies. This result was predicted because these three tools are core to the supply chain process that allows firms to be efficient when forecasting demand and managing customers' needs. In the Business Intelligence (BI) category, the most popular bundle included software-as-a-service (SaaS) and Infrastructure-as-a-service (IaaS) with over 27% of firms adopting them. SaaS is particularly important for small companies that don't want to build an infrastructure to manage their Information Technology (IT) needs. In the advanced manufacturing technologies, ERP and MRPII were the most popular bundles with 15% adoption rate while robots and Computer Numerical Control (CNC) were adopted by 7% of firms. Despite lower adoption rates in the manufacturing sphere, analyzing firms that planned to adopt suggested that 3D printing technologies were amongst the most popular. A similar result was observed for BI technologies with Big Data Software (BDS), which is a prerequisite to make AI implementation possible in the future. While in 2014, BDS adoption was low, there was a consistent increase in the adoption rate within the firms planning to adopt it.

By adding the temporal dimension to the previous association rules, there were important elements that were discovered. The apparent increase in planned BDS adoption translated in a low probability of adoption (confidence between 12% and 14%) when taking time into consideration. However, assuming that BDS and RTM are the same technology, the probability of adopting either one of these technologies increases to about 40%. The same results were observed with 3D technologies, where 3DM and 3DP each had around 16% chance of being adopted in the future. Combining all 3D printing technologies as a single technology, this number increases to 33%, suggesting that 1 out 3 of firms planned to adopt additive manufacturing technologies sometime in the future.

This study has some theoretical and practical implications. First, it was demonstrated that advanced technology adoption can have an endogenous effect on the propensity to innovate. This effect can be explained by the number of mitigating measures adopted to counter the obstacles to adoption, the CAPEX to name a few. Popular bundles of technologies that are adopted together were also observed. From a theoretical standpoint, it is the first time that a market basket analysis (MBA) is used to understand the behaviour of firms adopting advanced technologies that play a role in improving innovation performance. From a practical standpoint, it should be noted that while companies prefer to purchase technologies "à la carte", there are still some emerging patterns that could translate into best practices for firms looking at which technologies are best suited to their core business.

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LIST OF SYMBOLS AND ABBREVIATIONS

This list presents the symbols and abbreviations used in the thesis or dissertation in alphabetical order, along with their meanings. Examples:

BI	Business Intelligence
DIC	Design and Information Control
PF	Processing and Fabrication
MHSCL	Material Handling, Supply Chain and Logistics
PaaS	Platform as a Service
ICT	Information and Communication Technology
R&D	Research and Development
OI	Open Innovation
SME	Small-Medium Enterprise
KIBS	Knowledge-Intensive Business Service
TQM	Total Quality Management
ISO	International Standards Organization
AI	Artificial Intelligence
IoT	Internet of Things
TAM	Technology Acceptance Model
IDT	Innovation Diffusion Theory
RBV	Resource-Based View
TOE	Technology-Organization-Environment
SCT	Supply Chain Technologies
CT	Contingency Theory
BI&A	Business Intelligence and Analytics
CC	Cloud-Computing
AMT	Advanced Manufacturing Technology
MT	Manufacturing Technology
CRM	Customer Relationship Management
DF	Demand Forecasting

DP	Demand Planning
TMS	Transportation Management System
WMS	Warehouse Management System
SCCVS	Supply Chain Collaboration and Visibility System
AS	Automated Storage
RS	Automated Retrieval
QR	Quick Response
RFID	Radio Frequency Identification
ED	Executive Dashboard
BDS	Big Data Software
RTM	Real-Time Monitoring
SaaS	Software as a Service
IaaS	Infrastructure as a Service
CAD	Computer-Aided Design
CAE	Computer-Aided Engineering
CAM	Computer-Aided Manufacturing
VM	Virtual Manufacturing
ERP	Enterprise Resource Planning
MES	Manufacturing Execution System
SI	Software Integration for Quality R
MRP II	Manufacturing Resource Panning
EDI	Electronic Data Interchange
WCP	Wireless Communications for Production
WSN	Wireless Sensor Network
CIM	Computer Integrated Manufacturing
ASI	Automated Systems for Inspection
UAS	Unmanned Aerial System
FMS	Flexible Manufacturing Systems
FMC	Flexible Manufacturing Cells
LSR	Lasers (used in materials processing)

ROB	Robots without sensing or vision systems
ROBS	Robots with sensing or vision systems
CNC	Computer Numerically Controlled machinery
3DP	3D Printing for Plastics
3DM	3D Printing for Metals
3DO	3D Printing for materials Other than plastics or metals
AMST	Automated Machinery for Sorting and Transporting
PS	Plasma Sputtering
MM	Micro-Manufacturing
MEMS	Microelectromechanical Systems
VPN	Virtual Private Network
AXI	Automated X-ray Inspection
AOI	Automated Optical Inspection

LIST OF APPENDICES

CHAPTER 1 INTRODUCTION

Context and problem definition

In a world where the complexity of products and services is constantly evolving, firms need to adopt new capabilities and management practices to continuously improve their innovation performance and maintain a competitive advantage, which can be achieved by improving product quality, decreasing costs and life cycles and quickly adapting to constantly changing market demands. These practices can be part of what is called “organizational intelligence”, which allow a firm to learn from its environment (Lawson & Samson, 2001).

One way to learn from the external world is through the adoption an Open Innovation (OI) strategy. As defined by Chesbrough (2003a), OI is the use of a firm’s internal and external channels with the goal to participate in innovation activities. The open innovation term is vast and includes various concepts that are to be studied such as collaboration, cooperation and networks. In the literature, Golonka (2015) studies the concept of proactive cooperation and alliances portfolios. According to this study, cooperation must be done with stranger firms instead of allied firms in order to stimulate innovation. On the other hand, Samsonowa, Smirnova, and Zagorskaya (2012) combined the subjects of OI and collaboration in the same study to demonstrate their importance on the performance of a firm. Some scholars also highlighted some possible disadvantages of adopting an OI strategy including increased organizational complexity and increased costs (Manzini, Lazzarotti, & Pellegrini, 2017).

Another way for a firm to gain more knowledge is through the adoption of new technologies, especially in an era of Industry 4.0 (I4.0). The concept of I4.0 has been initially proposed in 2011 as a way to develop the German economy (Roblek, Meško, & Krapež, 2016). The three previous industrial revolutions were different in many ways: the first industrial revolution dates started in the late 18th century and was represented by mechanical production factories based on steam and water power; the second industrial revolution saw electricity enable mass production at the beginning of the 20th century; the third industrial revolution added a layer of automation to large-scale productions based on electronics and the Internet (Lukač, 2015). The main role of I4.0 is to optimize and improve the automation brought by the third industrial revolution. This can be done through various technologies encompassed by I4.0 (e.g., Internet of Things (IoT), Radio Frequency Identification (RFID), Artificial Intelligence (AI)) with the goal to collect as much data to enable near real-time decision-making. These technologies combined with cloud-based manufacturing can contribute to achieve a higher level of productivity as well as improving automation (Thames & Schaefer, 2016). There are many studies that focussed on the numerous technologies of I4.0 including IoT and smart manufacturing (Georgakopoulos, Jayaraman, Fazia, Villari, & Ranjan, 2016; Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014; F. Lin, Chen, Zhang, Guan, & Shen, 2015; Pfeiffer, 2016), but most papers only focus on a few technologies or sometimes one technology at a time.

The current literature lacks information on the complementarity that exists between the high number of technologies that firms can choose from. In addition, there are no studies that study the sequence of adoption of the different tools a company needs to adopt I4.0 technologies. This research uses the Survey of Advanced Technology (SAT) 2014 to explore a total of 37 technologies spread across four categories: Material Handling Supply Chain (MHSCL), Business Intelligence (BI), Design and Information Control (DIC), and Processing and Fabrication (PF). The aim is to cover on all the steps of the supply chain from the initial customer demand to the final production and packaging of a product. The survey was done across different industries in Canada and does not only focus on the manufacturing sector. With so many technologies to choose from, it is logical to believe that they should be many factors that will influence their adoption. Many theoretical models have proposed over the years to predict technology adoption, namely the technology-organization-environment (L. Tornatzky & Fleischer, 1990), the technology acceptance model (F. D. Davis, Bagozzi, & Warshaw, 1989), the innovation diffusion theory (E. M. Rogers, 1962) and the contingency theory (Donaldson, 2001). Other models that have also been applied to OI practices are used to study technology adoption. For instance, scholars have used the resource-based view of the firm to analyze the effectiveness of technologies (Crook & Esper, 2014). Absorptive capacity (W. M. Cohen & Levinthal, 1990) also plays a role in the adoption of advanced technologies because firms are required to have sufficient internal knowledge to integrate of a new technology (Narasimhan, Rajiv, & Dutta, 2006).

While the separate effect of OI and advanced technologies on innovation performance have been widely discussed in the literature, there is no study that evaluates, within the same model, their impact on the propensity to innovate. This thesis attempts to explore the role that OI and technology adoption can play on innovation propensity. To measure this, the survey provides four questions on whether firms introduced a product, process, marketing or organizational innovation. By using a probit model, with innovation being a binary variable, the results provide a propensity to innovate or, in other words, the probability of introducing an innovation.

There are two main gaps that were identified in the literature: (1) the impact of OI and technology adoption within the same model to explain innovation propensity; (2) the links between different technologies and their sequence of adoption in a I4.0 context. There are three research questions that need to be answered in an attempt to fill these gaps:

1. What is the impact of OI practices and advanced technology adoption on the propensity to innovate?
2. What are the complementarities between the 37 technologies that were reported in SAT 2014 and which bundles of technologies are Canadian firms adopting?
3. In which order are these advanced technologies being adopted?

The results will be presented in three separate chapters aimed at answering these three general questions. What is being measured or explored alongside the methodology chosen is presented in Figure 1.1. The first research question will be answered by using an instrumental-variable probit model that will include OI strategies, technology adoption as well as other business practices that can impact the propensity to innovate. The second research question aims to identify technologies that have been frequently adopted by using association rules. Finally, the third question is answered by expanding on the results of the second question in order to understand the sequence of adoption of these technologies. This sequence will provide insights into what is needed to adopt I4.0 technologies.

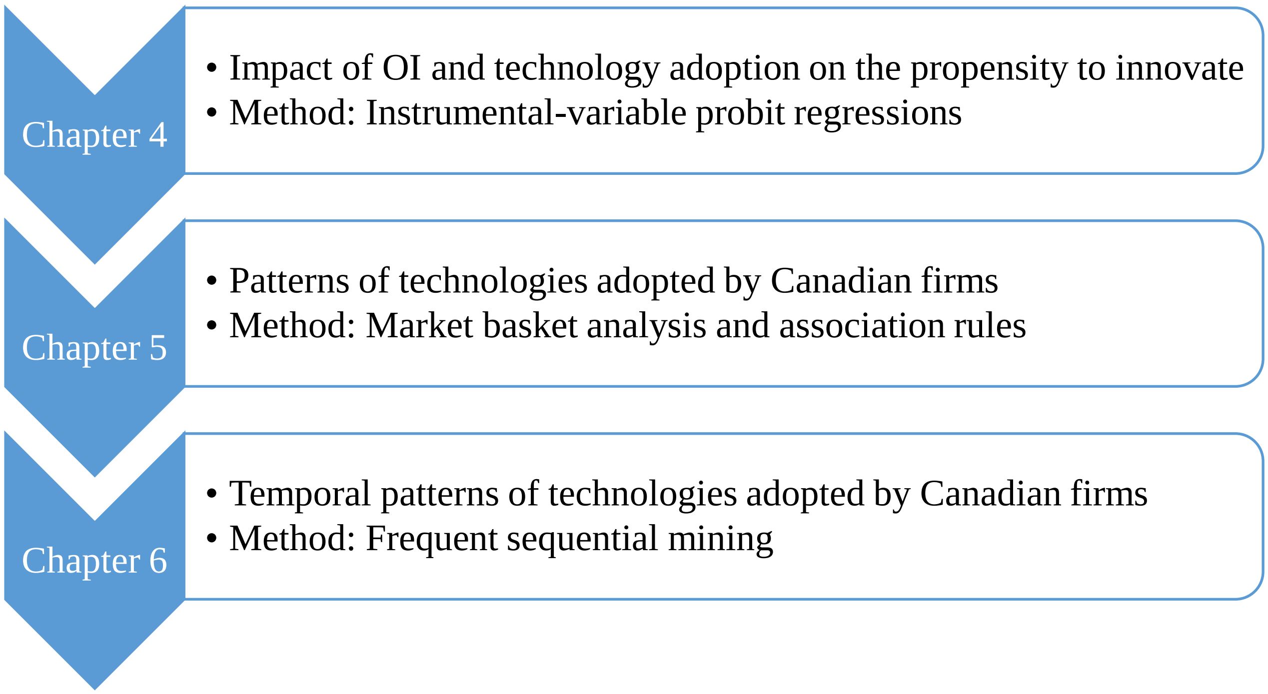
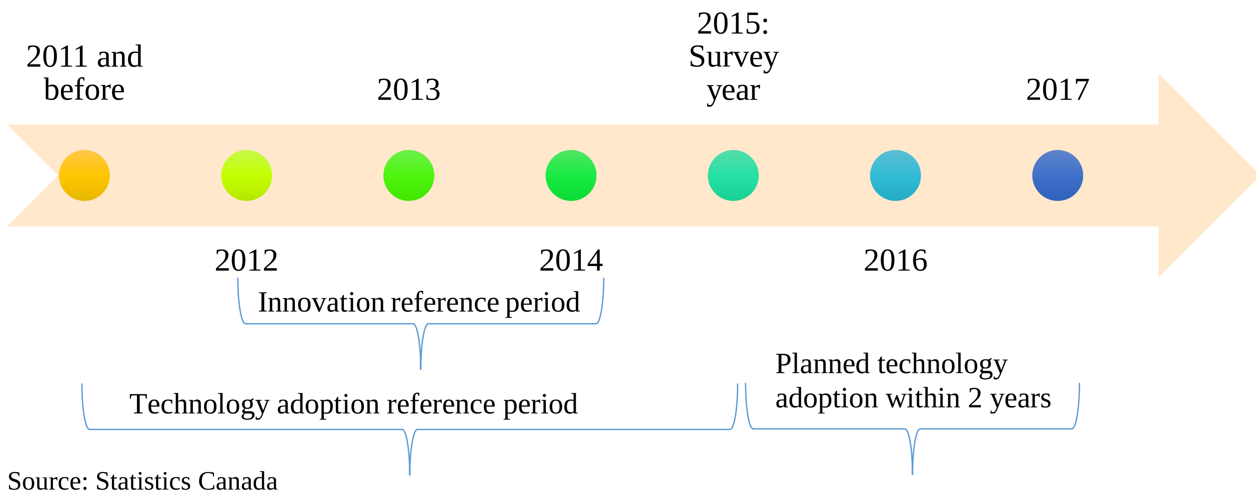


Figure 1.1: Path of methodologies and results in this thesis

The Survey of Advanced Technologies (SAT) 2014

The survey has been done in 2015 and its reference period is different for the questions regarding innovation and those regarding technology adoption. Because this study aims at understanding the impact between OI practices, technology adoption and the propensity to innovate, it is important to understand the timeline of the survey. The reference periods for when firms have introduced an innovation on the market and when they have decided to adopt a new technology can be found in Figure 1.2.



Source: Statistics Canada

Figure 1.2: Reference period in SAT 2014 for innovation and technology adoption

Not only is it possible to understand which families of technologies have an impact on innovation propensity, but the current and future patterns of technology adoption as well.

The rest of the thesis is structured in six chapters. In the second chapter, a literature review will be presented, focussing on the OI paradigm, the adoption of advanced technologies and their impact on innovation performance. The review will briefly cover the aspects of networks and proximities and how they are linked OI and advanced technologies. The third chapter will be devoted to a survey of all technologies that are studied in this research across four categories: Material Handling Supply Chain (MHSCL), Business Intelligence (BI), Design and Information Control (DIC), and Processing and Fabrication (PF). The fourth chapter will cover the research questions, objectives and hypothesis followed by a description of the methodology employed to answers the research questions. The next three chapters (chapters 5, 6 and 7) are dedicated to presenting the results of the study. First, chapter 5 focusses on the regression analysis that attempts to understand the link between OI, technology adoption and the propensity to innovate. Then, the sixth chapter explains the different complementarities found in each group of technology. Finally, the seventh chapter takes a similar approach to the previous chapter and adds a temporality aspect, aiming at explaining in which order are firms adopting advanced technologies. The final chapter will present a general conclusion and potential future research.

CHAPTER 2 LITERATURE REVIEW

This chapter discusses the literature review related to OI and the adoption of digital and advanced technologies. The first part of the chapter will be dedicated to defining the term innovation and explaining how its performance is measured according to the literature. The next part will focus on presenting the OI paradigm and how firms choose to adopt it. Furthermore, the review will attempt to make a link between the adoption of advanced technologies and OI. Finally, this chapter will explain how the adoption of OI jointly with advanced technologies influence a firm’s performance.

2.1 The concept of innovation

To be able to explain the open innovation paradigm, one must first mention the characteristics of an innovation. The definition that will be used for this thesis is the one presented in the fourth edition of Oslo Manual:

> An innovation is a new or improved product or process (or combination thereof) that differs significantly from the unit’s previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process) (OECD & Eurostat, 2019).

In addition to the general definition of innovation above, the following four types of innovation that are defined in the third edition of the Oslo Manual will be used:

> **Product innovation:** A good or service that is new or significantly improved. This includes significant improvements in technical specifications, components and materials, incorporated software, user-friendliness or other functional characteristics.

> **Process innovation:** A new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software.

> **Marketing innovation:** A new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing.

> **Organizational innovation:** A new organizational method in business practices, workplace organization or external relations. (OECD, 2005)

The common element is the novelty concept regarding what was put in place in the past. These four types of innovation are the core measurement of innovation in the Survey of Advanced Technologies (SAT) that are used in this research. However, according to the latest edition of the Oslo Manual, a new concept has been introduced that regroups process, marketing, and organizational innovations. In fact, a business process innovation is defined as:

> a new or improved business process for one or more business functions that differs significantly from the firm's previous business processes and that has been brought into use by the firm (OECD & Eurostat, 2019).

While these Oslo Manual definitions are the those measured in the survey, there are other perspectives mentioned in the literature, which are summarized in Table 2.1. For instance, some authors argued that innovation is the result of transforming knowledge into commercial value (Gunday, Ulusoy, Kilic, & Alpkan, 2011). Based on the OECD definitions presented above, a first perspective of innovation distinguishes between technological and non-technological innovations (Nelson & Rosenberg, 1993; OECD, 2005). Technological innovations represent product and process innovation while non-technological innovations refer to new organizational and marketing practices. This perspective also include the recent definition of business process innovation (OECD & Eurostat, 2019) A second perspective of innovation consists of the concept of disruptive innovation (C. Christensen, 2003), which is relevant for new products and processes. The third perspective considers innovation based on whether it is radical or incremental (Henderson & Clark, 1990). Radical innovation is very similar to disruptive innovation in the sense that is only applicable for products and processes. In contrast, incremental innovation can be applied to any type of innovation. Finally, Acosta, Acosta, and Espinoza (2016) considered open innovation (Chesbrough, 2003b; Huizingh, 2011) as a fourth perspective, which can be relevant to all types of innovation. Open innovation (OI) will be discussed in Section 2.2. The first and the fourth perspectives are measured in the survey. OI becomes an interesting dimension to study because the survey also provides information on whether firms collaborated or formed a strategic alliance with different partners.

Table 2.1: Innovation perspectives (adapted from Acosta et al., 2016)

Type of innovation	**Perspective 1**			**Perspective 2**	**Perspective 3**		**Perspective 4**
	Technological	Non-technological	Business process	Disruptive	Radical	Incremental	Open
Product	✓			✓	✓	✓	✓
Process	✓		✓	✓	✓	✓	✓
Marketing		✓	✓			✓	✓
Organizational		✓	✓			✓	✓

2.1.1 Innovation performance measures

There are many different innovation performance measures for firms and organizations (Prajogo & Ahmed, 2006). However, it remains a difficult question as there is no consensus in the literature (Hagedoorn & Cloodt, 2003). Considering that R&D activities are a possible path to innovation, a model that is based on the inputs and outputs of R&D presented by Brown and Svenson (1988) will be used. The model is shown in Figure 2.1 and provides a few examples of inputs, outputs and outcomes of R&D. The figure is simplified and adapted to this research. One element to weigh is the adoption of technologies as an input to help fuel R&D and ultimately the outcomes affecting innovation performance.

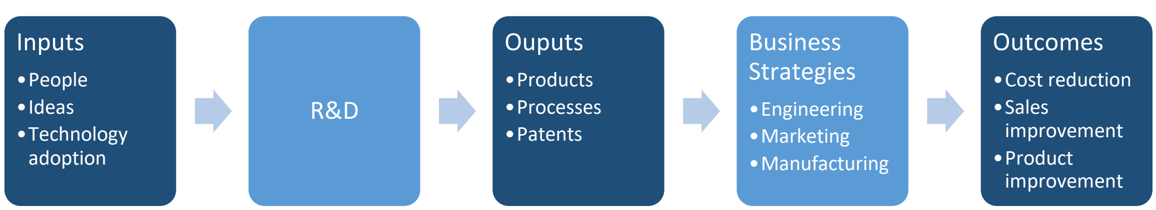


Figure 2.1: R&D inputs and outputs model adapted from Brown and Svenson (1988)

There are three dimensions recommended when measuring outputs: quantity, quality and costs (Brown & Svenson, 1988). To evaluate quantity, many authors suggest using the number of innovations developed during a specific period (Chiesa, Frattini, Lazzarotti, & Manzini, 2009; Prajogo & Ahmed, 2006). Other studies discuss the number of patents or the number of new products commercialized as a performance measure (Chiesa et al., 2009; Hagedoorn & Cloodt, 2003; Hsu, Lien, & Chen, 2015). Quality can be determined by three indicators being the speed at which the innovation is developed, their novelty level with regards to the market, and their technical performance (Chiesa et al., 2009; Prajogo & Ahmed, 2006). The speed and technical performance are more difficult to estimate by traditional surveys. In particular, empirical results are mixed when it comes to the relation between speed to market and product quality. Some authors found a moderate correlation between speed and quality (Kessler & Bierly, 2002), while others found an inverted-U shape relationship in which quality starts declining if speed to market is too high (Lukas & Menon, 2004). However, the novelty degree of innovation is widely discussed in the literature. There are three distinctions for the degree of novelty of innovation that is collected in surveys: (1) new at the firm level, (2) new to the local market, (3) new to global markets (OECD, 2005). Some authors use this measure to quantify the firm's performance described by the percentage of sales figures due to innovations new to the world, new to the firm and due to significantly improved products and processes (Laursen & Salter, 2006). This last example confirms what it is pointed out by the Oslo Manual (OECD, 2005) regarding the degree of novelty that is only pertinent to products and processes. In fact, the other two types of innovation (organizational and marketing) are internal to the enterprise and they are difficult to compare to the external world. Finally, the cost component can be measured by the percentage of sales due to new products (Chiesa et al., 2009) or the return on investment of these innovations (Brown & Svenson, 1988).

Some authors mentioned the need to take into consideration input, process and outputs measurements simultaneously (Carayannis & Provance, 2008). Innovation performance measures are also different in SMEs, when compared to larger firms (Saunila, 2017). More recent literature by Zheng, Li, and Wu (2013) posited two dimensions to the innovation performance: innovation efficiency which relates to the number of new products or their development speed amongst other measures and innovation profitability, which refers to the economic performance of innovation (cost reduction, the proportion of new product revenue, etc.). In terms of innovation performance, efficacy is defined as the degree of success of an innovation while efficiency refers to the effort required to reach the level of success (i.e. innovation efficacy) (Tseng & Tseng, 2016).

2.2 The Open Innovation Paradigm

In today's world, many firms already adopted some sort of open innovation practices whether they call it by that name or not. Collaboration, clusters or alliances are all terms that existed before the OI paradigm emerged in 2003. Since there are so many aspects to innovation that were already common practice for firms across various industries, this section will aim at reviewing the literature regarding those practices.

A lot of the OI papers are based on qualitative results, mostly case studies of big corporations. For example, Bigliardi, Ivo Dormio, and Galati (2012) did a multiple case study in the Italian ICT industry and they found that there were different ways to manage the OI model based on teamwork or tasks forces. However, the approach of operating can be proper to each company and this does not indicate whether OI increase the performance of a firm. Nowadays, it is clear that if companies do not innovate, do not continue to develop new products or processes constantly, they will ultimately fail (C. Christensen, 1997). This is especially true in the ICT sector where the technology is rapidly evolving. Since the technology is changing constantly, companies need to rely on safer and faster sources of innovation, and they need to collaborate with others in order to accelerate the innovation process. Their internal knowledge alone is not enough and this is why they need to combine them with external sources of information to develop new products (Chesbrough, 2003a). The search for external knowledge has been demonstrated as an important dimension to improve innovation performance (Stefan & Bengtsson, 2017). While many studies have acknowledged the promising nature of this paradigm (Chesbrough, Vanhaverbeke, & West, 2006; Gassmann, Enkel, & Chesbrough, 2010), some authors raised criticism regarding its potential conceptual ambiguities (Dahlander & Gann, 2010) and the impact of partners' collaboration on innovation performance (Brettel & Cleven, 2011; Stefan & Bengtsson, 2017). Increased costs and increased organizational complexity have also been noted in the literature as possible downfalls to the adoption of OI (Manzini et al., 2017). OI will be briefly defined along the different practices it involves in the next section.

2.2.1 Preliminary definitions of the concept

As mentioned, the term open innovation (OI) emerged for the first time in 2003. Chesbrough (2003a) defined OI as a new paradigm according to which organizations must use internal and external sources of ideas as well as commercialization processes to promote their technologies. This new concept is put in contrast with the traditional model of closed innovation. In this model, the firm manages its innovation process internally through all the cycles of product and services development. In his book, Chesbrough (2003b) discussed the idea that all the smart people do not work for the same firm in contrast with the closed model. This suggests that in order to get the best innovations, firms have to go outside their walls to exchange knowledge with other smart people that are not working for them.

Chesbrough proposes another definition of the paradigm in 2006 that states that OI uses "purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively" (Chesbrough et al., 2006, p. 1). Many authors refer to this new definition in their paper (Chiaroni, Chiesa, & Frattini, 2011; Gassmann et al., 2010; Huizingh, 2011). Following this definition, the inflows and outflows were defined as two fundamental concepts: the outside-in process (inflows) and the inside-out process (outflows) (Gassmann & Enkel, 2004). These concepts are very popular in the literature (Chiaroni et al., 2011; Dahlander & Gann, 2010; Huizingh, 2011) and were later referred to as inbound and outbound OI by Chesbrough and Crowther (2006). The blend of these two concepts is defined as a coupled process that is very applicable in the case of strategic alliances (Gassmann & Enkel, 2004). However, it is worth noting that they imply that the paradigm is not necessarily viewed similarly by everyone because of the multiple dimensions it contains. In fact, it must be viewed as a continuum with different levels of openness (Dahlander & Gann, 2010). In other words, a firm will certainly be doing OI activities but it's a matter of understanding to which extent these practices are in place. The idea that there are different levels of openness is also shared by many other authors (Keupp & Gassmann, 2009; Laursen & Salter, 2006). The different strategies can be summarized in the following table (Table 2.2) based on the work of Gassmann and Enkel (2004):

Table 2.2: Core Processes of open innovation based on Gassmann and Enkel (2004)

Process	Practices
Outside-in	Integrating External knowledge, customers and suppliers
Inside-out	Bringing ideas to market, selling/licensing IP and multiplying technology
Coupled	Coupled outside-in and inside-out process, working in alliances

2.2.2 Inbound open innovation (outside-in process)

The inbound strategy consists of looking for external sources of knowledge in order to develop new products internally. In order words, inbound OI is the use of outside knowledge internally (Huizingh, 2011). The intent of this strategy is for a firm to integrate outside competences in its own innovation process. According to Enkel, Gassmann, and Chesbrough (2009), it allows a firm to learn new knowledge at a lower cost than if it was to develop it from scratch. The reduction of costs in acquiring new capabilities and technologies makes it one of the main reasons to use inbound OI. In fact, companies are now required to go outside their walls to be able to develop and learn new knowledge in a much cheaper and faster way. There are many possible practices of inbound OI discussed in the literature that will be presented below.

The integration of customers and suppliers has widely been discussed in the literature (Gassmann, 2006; Gassmann & Enkel, 2004; Isckia & Lescop, 2011; van de Vrande, de Jong, Vanhaverbeke, & de Rochemont, 2009). However, the practice was introduced long before the OI paradigm. The novelty with OI is that suppliers and customers must be integrated early in the innovation process (Gassmann, 2006; Gassmann & Enkel, 2004).

Another strategy of OI is to invest in start-ups (van de Vrande et al., 2009). Without having to spend a lot of money to acquire all its knowledge, it allows the firm to stay in touch with new technologies. The next step is the acquisition of licenses or other firms as well as R&D subcontracting (Gassmann, 2006; Isckia & Lescop, 2011; U. Lichtenthaler, 2009; van de Vrande et al., 2009). It is one of the core practices of OI because it allows a firm to gain external knowledge and competences at a reduced cost (Gassmann, 2006; van de Vrande et al., 2009). For example, if a firm has invested in a start-up that developed a very useful technology, this firm may decide to acquire a license or buy the whole company.

Some of these practices may be challenging for smaller firms and this where they might require the support of an intermediary (Gassmann, Daiber, & Enkel, 2011; Nambisan, Bacon, & Throckmorton, 2012). Intermediaries play an effective role in OI especially in the development and creation phases (Janssen, Bouwman, René van, & Timber, 2014). They help firms with IP management (Chesbrough, 2003a) and support them in acquiring external knowledge (Nambisan et al., 2012).

Finally, a great practice of inbound OI is the use of crowdsourcing. It is widely discussed in the literature as a way of gathering ideas from different external sources (Chesbrough & Brunswicker, 2013). Howe (2008) described crowdsourcing as submitting a problem to a large audience. These challenges can be accessible internally to a firm or to other firms and the general public (J. R. Davis, Richard, & Keeton, 2015).

2.2.3 Outbound open innovation (inside-out process)

The outbound strategy consists of leveraging internal knowledge with the outside world by finding a firm that is better suited to commercialize a product, for example. Huizingh (2011) defines the inside-out process as a way to externalize internal knowledge and ideas. One of the perfect examples to explain this practice is the acquisition of licenses or patents from another firm. According to Isckia and Lescop (2011), a large number of patents are not really used in a firm's products; they are simply proactive, so a firm can protect its IP. However, these patents can be sold or transferred to other firms that are more suited to commercialize them. This value generation from unused patents is a strategy that is particular to an open business model (Isckia & Lescop, 2011). This practice should be integrated to the business model when a firm decides to adopt the paradigm (Chesbrough, 2003b, 2006; Gassmann, 2006). In the case of patents not suited to be commercialized in a certain firm van de Vrande et al. (2009) discussed the concept of spin-off.

Instead of selling patents to the external world, a firm may decide to create a start-up that will be managed independently.

2.2.4 Coupled process and conclusion

The coupled process is the third aspect identified by Gassmann and Enkel (2004) and consists in a combination of the two previous processes presented. The most frequent examples are in the case of strategic alliances (U. Lichtenthaler, 2008a), co-enterprises (Gassmann & Enkel, 2004) and collaborative R&D between partners (Gassmann & Enkel, 2004).

By definition, an inbound effort from an organization will always generate an outbound effort from another organization (Chesbrough & Crowther, 2006). Despite this definition, it seems that in most studies, inbound OI is the most used practice in the literature (Chesbrough & Crowther, 2006; Chiaroni et al., 2011; U. Lichtenthaler, 2015). According to Huizingh (2011), this might be the case because organizations provide less internal knowledge than the external knowledge they use. In fact, it could be that a lot of organizations are accessing similar external knowledge that is available while keeping secrets from others. Another possible explanation is the fact that universities develop a lot of technologies that are sold or given to the industry to be commercialized. Dahlander and Gann (2010) discussed that this practice is considered a “non-pecuniary” interaction. On the other hand, inbound OI seems to be the most used practice because it might be the most effective for firms. This leads to the fact that some practices are more effective than others and depending on the firm’s innovation strategy these practices will vary. Inbound OI is also the most studied process in the literature (Enkel et al., 2009; Michelino, Cammarano, Lamberti, & Caputo, 2015). Finally, despite the emergence of this term in 2003, a lot of these practices were used by firms before in a certain sense. Some authors mention that OI is not a new concept in practice (Huizingh, 2011; Mortara & Minshall, 2011) while others criticized the fact that it is “old wines in new bottles” (Trott & Hartmann, 2009).

2.2.5 The adoption of open innovation

According to Huizingh (2011), there are two types of motives why firms would choose to open up their processes. The first one is an offensive strategy to stimulate growth while the second motive is more of a defensive strategy meant to share risks and costs with an external partner.

OI studies have been focussed across all industries. For example, some studies looked at the adoption of OI practices in the ICT industry but most of them were qualitative (L. Bengtsson & Ryzhkova, 2013; Grøtnes, 2009; Rohrbeck, Holzle, & Gemunden, 2009). Other studies have used quantitative data to study R&D cooperation and supplier innovativeness (Samsonowa et al., 2012; Sun, Zhou, Lin, & Wei, 2013). Furthermore, the application of OI is dependent on the business strategy rather than the trend in the industry (Keupp & Gassmann, 2009) which indicates that the internal environment is more important than the outside world (Huizingh, 2011). This means if some firms are not equipped internally to open up their processes, they will not adopt this business model just because it is trending amongst other firms. It would be interesting to find out if there are firms that are pioneers of OI in this industry.

To summarize, there are two important concepts that are widely present in the OI literature. First of all, outbound OI is more used and proved to be more effective than the inbound practice. Second, the internal environment is more important than the outside world. This means that if a firm wants to adopt an OI model, it needs to have the resources and the needs to follow this business strategy. Once this is set, a firm can now look for external sources of knowledge to complement what it has internally without the need of sharing anything in return. In some industries, it might be more difficult to collaborate and adopt OI practices. Following a study by Letaifa and Rabeau (2013), it is clear that there is a social distance preventing ICT service providers from collaborating which is resulting in cheating and the refusal to share resources. The concepts of clusters and proximity will be discussed further in the text. Schroll and Mild (2012) made a literature review of the empirical quantitative studies related to the adoption of OI. They compared the different methods of data collection and found that most studies used European innovation surveys (CIS) as their source of data.

A firm might decide to adopt OI proactively based on certain factors but according to J. F. Christensen, Olesen, and Kjær (2005), firms tend to react to the challenges of their external environment which they respond to by adopting OI. U. Lichtenthaler and Ernst (2009a) found that industry characteristics do not influence the level of OI adoption. This means that all industries could adopt this model including sectors that are more reluctant to do so. Furthermore, in a study in 3 European countries (Germany, Austria and Switzerland), Drechsler and Natter (2008) found that out of 240 firms, 76% adopted OI (by using outbound and inbound strategies) across all industries. Similar studies have been conducted over the years in different countries and industries, but none have found such a high rate of adoption.

Whether firms adopt OI or not, there are still innovation barriers that prevent them from developing and commercializing the products they want. S. Lee, Park, Yoon, and Park (2010) made a list of the 10 most reported barriers in both SMEs and large firms. They found that SMEs and large firms do not share the same difficulties at all and that the two may be complementary. For instance, large firms find that their R&D department has no power while this doesn't seem like an issue for SMEs which is normal. Other authors explored the strategies for overcoming the barriers to value creation in the nanotechnology sector (Maine & Garnsey, 2007). These barriers may be more obvious for process innovations when compared to product innovations, especially when it comes to value creation (Maine, Lubik, & Garnsey, 2012). Analyzing Reiner (2008)'s approach to the different stages of a firm, an SME can be categorized in the childhood stage when a start-up has successfully been able to commercialize a new technology. This means that an SME is still relatively small and its organization is not as rigid as a large firm which makes it more inclined to innovate. Large firms are usually embedded in a political environment and depend on market economics and if there is not an immediate return from a technology, there won't be any investment (Reiner, 2008). This leads to think that there are more radical innovations in SMEs or start-ups compared to large firms. On the other hand, large firms remediate to this by acquiring knowledge and IP from smaller firms. For instance, the nanotechnology sector has seen this phenomenon where large firms possess a disproportionate number of parents (Avenel, Favier, Ma, Mangematin, & Rieu, 2007). However, instead of commercializing these patents, large firms prefer to acquire start-ups that have demonstrated commercial value and overcome technological uncertainty (Chesbrough, 2003b; Maine, 2008).

As was previously mentioned, smaller companies usually don't have the resources to do everything, so they require intermediaries and external partners to help them. In fact, smaller companies seem to use open innovation in the last steps of the innovation process, especially when they need to commercialize a new technology (S. Lee et al., 2010). This is particularly true considering they don't have the financial resources to commercialize a technology, so they must look outside. Gassmann et al. (2010) believe that the internal process of OI is still trial and error. Firms will try different practices and adapt to their external environment. This being said, firms that are not able to find external sources of information can require the help of an intermediary. Nowadays, some firms have an integrated OI process while others are still trying out the different practices. Today, most organizations are aware of OI practices even though they might not have a structured process yet. However, in the near future the term OI will fade away because it will have been fully integrated in a firm's innovation management (Huizingh, 2011). The more firms that integrate this model, the more other firms will follow.

It is logical to think that the larger the firm, the easier it is to apply OI practices because of the network it may have. A large company will have a big network with many different actors, mainly suppliers and other firms with whom it may be allied. When a firm cannot build its own network, it can have access to an intermediary that will already have a network of multiple players. Whether it is a private organization, an individual or consultants (Aoki, 2001; J. Howells, 2006), an intermediary is an entity that organizes a network and builds trust between its members, which is important for SMEs especially (S. Lee et al., 2010). Intermediaries play an effective role in OI especially in the development and creation phases (Janssen et al., 2014). Most companies in Canada are small businesses. Therefore, these small firms might not have all the resources they'll need to progress on their own. They need to build an organized network in order to focus on maintaining deep and lasting relationships with partners (Simard & West, 2006). These firms also need to search for competitors, collaborators and customers in the markets (Makadok & Barney, 2001) but they can't afford professional intelligence for scanning their environments the same way larger firms do (E. Lichtenthaler, 2003). Therefore, S. Lee et al. (2010) propose an intermediary model that supports SMEs to create their collaboration network in order to maximize their chances of innovation. According to Watkins and Horley (1986), intermediaries can play important roles in technology transfer when it comes to the partner selection process by providing support to sign a contract with those partners. Contracts will formalize an informal collaboration (Shohet &

Prevezer, 1996). Some intermediaries such as Knowledge-Intensive Business Services (KIBS) also support innovation in firms who use their services (Wood, 2002).

2.2.6 Types of knowledge and information sources

It is logical to believe that if OI had a role to play in the survival of some companies, they must have been adopting this business model before the term OI existed. It is rather simple to demonstrate that by mentioning the clusters because they existed a long time before OI. Their main purpose was to foster collaboration between firms of the same industry and increase their innovation performance level. Clustering is a form of OI because the firms inside it use outside knowledge to complement their internal processes and the other way around is also true. Whether it is with clusters or with an OI business model, firms will aim at exchanging information. They will aim at researching and exploiting different sources of knowledge.

There are 3 major types of knowledge as identified by Leonard-Barton (1998): public specific, firm-specific and industry-specific. A firm needs to create and maintain relationships with diverse actors in order to acquire these types of knowledge (Bigliardi et al., 2012). For example, a firm that have good relations with suppliers can get industry-specific knowledge while a firm can get scientific or public knowledge from universities or through an open platform, respectively. These relationships are important for various reasons, one of them is that firms are able to share costs and risks when developing a new technology (Buganza & Verganti, 2009; Nieto & Santamaría, 2007). Sharing costs will imply that firms are more likely to try riskier and radical innovations if it has the potential to be commercialized. Types of knowledge can also influence the adoption of advanced technologies based on an industry’s best practices. Technology adoption will be discussed later in the review. Another way to view R&D and OI practices is in 3 types of knowledge processes as defined by U. Lichtenthaler and Lichtenthaler (2009), which are exploration, retention and exploitation. They can all be performed internally or externally which makes six processes that can consist of different innovation strategies. It is still unsure if firms need to develop all 6 strategies or can only focus on a few of them (Huizingh, 2011; U. Lichtenthaler & Lichtenthaler, 2009). Knowledge can come from different sources of information, which are described in the next section.

These sources of information can be internal (e.g. R&D, employees), external or on the market (e.g. suppliers, competitors, customers), institutional (e.g. universities and governments) and public (e.g. conferences and journals). Despite all the openness that is encouraged for firms to innovate, internal R&D remains an important aspect. According to Sun et al. (2013), firms who had a strong internal R&D showed an increase in their innovativeness when they used subcontracting to do more research. These results suggest that a firm must be able to have enough knowledge internally to absorb the knowledge coming from outside. A firm cannot only rely on others but needs to have a solid foundation in order to start collaborating with the external world. According to Dahlander and Gann (2010), firms continue to invest in internal R&D because of two main reasons. The first one is that firms who invest in internal R&D benefit more from spillovers because firms require internal knowledge to be able to absorb external knowledge (W. M. Cohen & Levinthal, 1990). The second reason is that a firm with internal R&D is attractive to the outside world (Rosenberg, 1990). In other words, a firm will be able to find potential partners if it has a good capacity to absorb all the required information. The absorption of this knowledge is dependent on internal expertise and information that is already acquired. Therefore, internal R&D must be viewed as a complement to OI (Dahlander & Gann, 2010) although it can also be viewed as a substitute when firms are limited in their R&D and need to compensate with external resources (Chesbrough, 2003b).

The credibility built by firms via their internal R&D will play an important role in the partner selection process. According to Nieto and Santamaría (2007), the selection of relevant partners is an important concern in R&D collaboration. The more partnerships these firms build, the more they learn about collaboration and how to build more partnerships (Heimeriks & Duysters, 2007). However, this can increase the cognitive proximity as described by R. Boschma (2005) which will decrease the innovation performance of the firms involved. The most common type of partnership is a vertical cooperation (e.g. suppliers and customers) while horizontal cooperation (e.g. competitors and institutions) is less common because of the risk and barriers it presents (van Beers & Zand, 2014). It is always risky when cooperating with a competitor because a firm would not want to give some valuable information and lose the competitive advantage. Furthermore, when it comes to institutions or universities, they usually develop a product without the commercialization in mind. This leaves companies with a product that cannot be marketed resulting in unnecessary costs.

Part of the OI paradigm is not only opening locally, but also globally because knowledge can be found everywhere. This brings the concept of foreign collaboration in R&D. The importance of collaboration with foreign customers and suppliers is expected to lead to new products and stimulate innovation (Eisenhardt & Schoonhoven, 1996; Gulati, 1999; Lavie & Miller, 2008). Nowadays, firms have multiple possibilities when it comes to R&D collaboration. Miotti and Sachwald (2003) have made a list of actors involved in cooperative R&D activities. They found interesting results segmented between larger firms and SMEs. They studied the aspect of foreign partnership finding that larger firms in high-tech sectors are more likely to go this direction while French firms (the firms targeted by this study) were more likely to stay local, thus collaborating with French or European firms. They also found that firms that cooperate with the US are looking for complementary R&D knowledge while firms who only cooperate on the European continents do it to share the costs. This leads to think that foreign partnership is better than local partners because there is a cognitive distance that favours innovation. It is also why firms who collaborate with US partners do it because there is a technological barrier in their innovation process, and they are looking for complementary knowledge. On the other hand, firms that collaborate on the local or national level are looking for partnerships to share costs, meaning that they already have similar processes and knowledge.

As was previously mentioned, vertical cooperation has a positive impact on innovation and there are a few studies that demonstrate that. A collaboration with suppliers especially can have a huge impact on the innovation performance of a firm. In an Irish study of ICT and high-tech firms, Jordan and O'Leary (2007) found that a greater interaction with suppliers and customers led to an increased level of innovation. On other hand, they also found that the interaction with Higher Education Institutions (HEI) did just the opposite. This could be the case because universities do not have commercialization in mind when doing research. Even though most universities have a license transfer office, it does not bridge universities to firms effectively and there is no communication happening between both parties until the end of the research which makes most products hardly marketable. However, according to Golonka (2015), firms that cooperate with “strangers” instead of friends enhance their innovativeness. This also reinforces the concept of foreign collaboration described earlier and is directly related to cognitive proximity. Firms will tend to have better communication and understanding with other firms with whom they are already allied, and this might lead to a lack of innovation. Whether the other players are strangers or friends, there are many scholars who suggest that firms that collaborate with a variety of external partners are expected to enhance their innovation performance through the acquisition of complementary knowledge (Belderbos, Carree, & Lokshin, 2006; Laursen & Salter, 2006; Nieto & Santamaría, 2007; van Beers & Zand, 2014). For instance, Laursen and Salter (2006) introduced the concepts of breadth and depth. The former is defined as the number of external sources a firm utilizes in order to enhance its innovation activities. The latter consists of how deep the relationship is between the firm and each external source. This can be compared to a network one person might have. The more people this person has in its network; the less deep relationships this person can have.

The concepts of functional and geographical diversity are presented by van Beers and Zand (2014) as cooperating with actors in different functional groups and in different locations respectively. They found that geographical diversity is more important to incremental innovation while functional diversity is more important to radical innovation. When firms get information from various sources, it allows them to have different perspectives on a certain problem which promotes radical innovation. However, geographical diversity implies foreign partnerships and firms will tend to get information that they do not have to develop an improved product that already exists.

A study by S. A. Chung and Kim (2003) shows that firms who collaborate with suppliers improve their quality and enhance their innovation performance. The diversity suppliers will result in firms acquiring a variety of knowledge, which will need to be integrated within a firm internal knowledge base. The ability of a firm to absorb this knowledge and be able to commercialize it will have a positive impact on its innovativeness (W. M. Cohen & Levinthal, 1990). Furthermore, W. M. Cohen and Levinthal (1990) argue that individuals in a firm are able to make new links with diverse sources of knowledge. This supports the idea that the more diverse the sources of knowledge are, the better the complementarity that emerges from it. This also stimulates the participation of all employees in the innovation process of a firm since they can have various information individually that may not be found outside. However, Clausen (2013) found that the absorptive capacity of a firm is limited and can reach saturation very quickly. This may be a source of explanation for the results that Laursen and Salter (2006) found concerning the non-linear relation (inverted U-shape) between the breadth & depth and a firm's performance.

In sum, firms need to select accordingly their partners and which knowledge they want to acquire because their capacity to assimilate new information is limited. The more internal knowledge a firm has, the more external knowledge it can absorb. Firms can develop new information internally by performing R&D activities which are thought to increase their absorptive capacity (W. M. Cohen & Levinthal, 1990). Firms can also get information from their employees by letting them participate in the innovation process through an online platform or through round tables. It is clear that suppliers, competitors and customers can play an important role in increasing a firm's knowledge and thus helping in the innovation process as well. To be able to gain access to knowledge, firms need to find a way to cooperate with external actors. The next section will focus on presenting the different types of interactions a firm can have in order to gain access to the difference sources knowledge whether it is internal, external and from institutions.

2.2.7 Types of interactions

Actors can interact in many ways in order to exchange knowledge and information. To increase its competitive advantage, a firm needs to rely on the strength of its network and its relationships with other firms (Y. Lee & Cavusgil, 2006). This section will briefly review the different types of interactions ranging from cooperation to alliances and contracts. According to James H. Love and Roper (2004), collaboration and cooperation are two terms that are used interchangeably to describe an interaction between two (or more) individuals or organizations. However, some scholars find that the distinction between both terms is important (Paulus, 2005; Polenske, 2004).

Collaboration is defined as the participation of two parties or more in the design, manufacturing, or commercialization of an innovation (Polenske, 2004). In other words, it describes the action of two parties working together develop a product (or a process). On the other hand, Polenske (2004) defines cooperation as an agreement between two or more parties in order to share common resources (e.g. human or financial). According to Hord (1986), collaboration implies that activities are shared between two parties which is why it takes more time to maintain this strategy compared to cooperation. Although collaboration implies an exchange of tasks resulting in an exchange of information (Hord, 1986), both strategies can be considered as OI practices. In the case that two competitors decide to cooperate, M. Bengtsson and Kock (2000) discuss about the concept of “coopetition”, which they consider as complex relationship because it involves two conflicting logics of interactions. Furthermore, coopetition rarely focusses on design, manufacturing, or commercialization of a product (Polenske, 2004). Firms will tend to reach an ideal relationship consisting of a low level of competition while practising a high level of cooperation although studies show that if both levels are high, the relationship can also be effective (Wilkinson & Young, 1994).

Partnerships

By definition, partnerships are a strategy that two firms may use when they have common goals and share a mutual benefit (Mohr & Spekman, 1994). Alliances and partnerships are two terms that are often used interchangeably in the literature although they are not the same (Glover & Wasserman, 2003). According to Black’s Law Dictionnary, a partnership is defined as follows:

> A voluntary contract between two or more competent people to place their money, effects, labour, and skill, or some or all of them, in lawful commerce or business, with the understanding that there shall be a proportional sharing of the profits and losses between them. (Garner, 2009)

The most important difference between the two is that partnerships occur when two firms share ownership while alliances happen when they share a common goal. Both can be controlled by contracts although it’s more usual for alliances. Partnerships can take two different forms, either contractual based or relationship based. Contracts are a form of agreement used between two parties to formalize a collaboration. They are used for all kinds of purpose namely between a buyer and a seller so both actors can be aware of the terms of an agreement. A written contract that was signed by both firms ensures that the terms of the transaction will be sanctioned by laws if not respected (Ring & Van de Ven, 1992). Some contracts might even address how different situations or conflicts might be treated if they arise in the future (Lusch & Brown, 1996). Contracts will reduce the risks related to a partnership (Y. Lee & Cavusgil, 2006) because they represent obligations that both parties must honour to respect the terms of the agreement (Macneil, 1977).

Partnerships can also be based on the relationships between two firms. One of the most important aspects of a relation is mutual trust because it can facilitate learning and knowledge transfer (Kale, Singh, & Perlmutter, 2000). As discussed, opportunistic behaviours from a firm can be protected by a contract but mutual trust can reduce the fear related to this kind of behaviour (Gulati, 1995). According to Kale et al. (2000), mutual trust can also promote and accelerate the transfer of knowledge between 2 firms which will be reinforced by knowledge-sharing sessions (Dyer & Singh, 1998).

Strategic Alliances

An alliance is based on partnership which can be based on a relationship or a contract. Strategic alliances are the next step of partnerships when firms are ready to collaborate on a longer term. One of the main reasons on why firms would choose to form an alliance is to exchange complementary assets or information (Nohria & Garcia-Pont, 1991). This can happen in R&D when a firm has a certain specialization that the other firm hasn't. For example, one firm can have an expertise in the hardware of a product while to other firm works on the software part. Instead of spending money on developing a software department, the first firm will share costs and risks with the other. This cost sharing is very beneficial when 2 or more organizations work on very expensive projects (Hagerdoorn, 1993). Less risk means that a firm has more chances of surviving in case the project fails. For this reason, alliances increase the survivability rate of an organization (Baum & Oliver, 1991; Mitchell & Singh, 1996). Alliances can also provide opportunities for a firm to enter new markets (Mitchell & Singh, 1992), which will have a positive impact on the growth rate of the firms that are implicated (Powell, Koput, & Smith-Doerr, 1996).

In a study by Stuart (2000), it is demonstrated how alliances can convey a social status and recognition to the firms involved. He also found that alliances with large firms turned out to be the most valuable because of the resources they possess and the reputation they already have. Typically, a large company that has a good reputation will attract the others. Furthermore, organizations with alliance experience are most likely to form a successful alliance (Deeds & Hill, 1996). With experience, a firm can better manage a conflict situation that may arise (Mohr & Spekman, 1994). Whether an alliance is successful or not, firms will tend to learn from it and thus, acquiring more experience. This will lead to better alliance management and partner selection processes as well (Simonin, 1997). In a study led by Heimeriks and Duysters (2007), it is demonstrated how experience affects an entire alliance portfolio. In other words, lessons learned in an individual alliance will have a positive effect on the success of other alliances a firm may have.

2.2.8 Open innovation according to the type of innovation

The type of innovation can be a determining factor in the way OI will be applied. High-tech industries are focussed mostly on product development. However, there are also some firms that provide services to customers and businesses. Process innovations are less visible as they are mostly internal to these firms. This section will focus on presenting the difference between the three types of innovations.

Open innovation in product development

As a reminder, the Oslo Manual (OECD, 2005, p. 9) defines a technological product innovation as follows:

> the implementation or commercialization of a product with improved performance characteristics such as to deliver objectively new or improved services to the consumer.

Unlike services and processes, a new product is generally physical and requires codified knowledge which implies that it can be protected by patents. A lot of firms are exploiting their customer’s idea to develop new products (Ettlie & Rosenthal, 2011). One of the practices of OI in product development is living labs. A Living Lab is defined by Pierson, Lievens, and Ballon (2005, p. 5) as follows:

> An experimentation environment in which technology is given shape in real life contexts and in which (end) users are considered as co-producers.

Therefore, users are not only a source of innovation but they play a crucial role in the innovation process (E. Von Hippel, 1976). The market is getting more competitive for companies and product life cycle has shortened (Poiesz & van Raaij, 2002) and therefore, OI becomes a necessity to accelerate the product innovation process. One of the other ways of applying OI in product development is through universities and suppliers. Through technology transfer mechanisms and with IP protection, universities can participate in all three stages of an innovation cycle. Jordan and O'Leary (2007) found that a greater frequency of interactions with suppliers and customers led to a higher probability of product innovation. Unlike services, which are not physically quantifiable (Gallouj & Savona, 2009), products have a tangible nature and they can be easily codified and transferred to another firm or organization. This is a major advantage of product innovation along with the fact that customers can have a say in the innovation process as well. For instance, customer co-creation (Prahalad & Ramaswamy, 2000) is a way for firms to collaborate directly with customers.

Capturing value from product innovation relies almost entirely on the business model (Chesbrough, 2003b, 2006). For this reason, licensing IP and buying external technology are not enough for product development anymore, hence the need for a company to open its business model (Chesbrough, 2007). In a review on open business models, Chesbrough (2007) presents three successful cases who opened their business model (P&G, Air Chemicals, IBM) confirming the important role of OI in product development. Despite all the positive aspects of this paradigm, opening up can still be challenging because companies may not be sure which IP to use. With patents, knowledge is easily codified and disseminated to the external world but with reverse engineering and risks of leakages, a company might lose its competitive advantage. Other types of partners can also supply new ideas for final products, such as suppliers, consultants and even competitors (Huston & Sakkab, 2006). For instance, companies can obtain new technologies from their suppliers (Yeniyurt, Henke, & Yalcinkaya, 2014). Finally, firms can also choose to acquire products in order to quickly estimate the size of a new market (Franke & Schreier, 2010; E. A. Von Hippel, 2005).

Open innovation in process development

As was previously mentioned, the OECD (2005, p. 9) defines process innovation as follows: the implementation/adoption of a new or significantly improved production or delivery method. It may involve changes in equipment, human resources, working methods or a combination of these. The adoption of a process view of the business combined with new or improved processes will help firms reduce their costs and time as well as improve their business objectives (TH Davenport, 1993). According to Utterback and Abernathy (1975), a process is employed to produce a product or a service and can include work and information flows as well as task specifications. In other words, a process innovation aims at increasing the productivity (or quality) at which a product or a service is delivered. Therefore, a process is mostly internal knowledge and can be a mixture of both tacit and codified knowledge. However, a process is generally protected by trade secrets (J. R. Baldwin & Hanel, 2003) so the outside world can’t really see the difference if a firm introduced a process innovation. Developing new processes requires different commercialization strategies when compared to product innovation (Linton & Walsh, 2008). Unlike a product or a service innovation, the customer of a process innovation is the firm itself and its employees (unless the process is exported to other organizations). Branstetter (2018) found that there is a high amount of manufacturing patenting in developing economies, which could mean that process innovation are more prominent in these countries (Fuchs, Combemale, Whitefoot, & Glennon, 2020).

Frequent interactions with suppliers resulted in increased process innovations (Jordan & O'Leary, 2007). A company might look outside its boundaries to find best in class processes and try to apply them to its business model. Process innovations, such as Total Quality Management (TQM), Six Sigma or ISO 9000, were known as the most important managerial innovations in the 2000s (Cole & Scott, 2000). Process improvements depend on internal and external customer satisfaction (Benner & Tushman, 2002). Rigid processes will help increases efficiency in a firm but may involve a lot of change management because one change in the system will affect everything else (Hannan & Freeman, 1984; Tushman & Romanelli, 1985). This is why a lot of process innovations are only incremental (Adler, 1993; Anderson, Rungtusanatham, & Schroeder, 1994). West and Gallagher (2006) wonder what role OI can play in process innovations. In fact, many of the OI strategies described for product development can also apply in this case. For instance, collaboration with external partners enables a firm to gain access to new knowledge (Dyer & Singh, 1998) that can be absorbed to increase the propensity to introduce new processes (Un & Asakawa, 2015). Moreover, suppliers can act as technology and know-how providers to firms seeking to advance their new work development projects (Potter & Lawson, 2013). This type of collaboration requires the sharing of tacit knowledge that can complement a firm's internal processes (Siguaw, Simpson, & Enz, 2006). Furthermore, external R&D is another instrument to acquire knowledge that may be eventually amalgamated to existing knowledge resources (Barthélemy & Quélin, 2006), which can be achieved through the process of absorptive capacity (Lane, Koka, & Pathak, 2006). Other strategies that do not involve direct cooperation with external partners can also be used to enhance current processes. One can monitor an internal or external blog where individuals share their opinions on a certain topic (Droge, Stanko, & Pollitte, 2010), which can then be integrated in the development of new products and processes (Benner & Tushman, 2003).

Open innovation in service development (e.g. marketing, organizational innovations)

Innovation in the service sector is attracting a lot of attention but the larger the sector, the larger the gap is going to be (Djellal & Gallouj, 2010). According to Gadrey, Gallouj, and Weinstein (1995, p. 5), a service innovation can be defined as follows:

> organize a solution to a problem (a treatment, an operation) which does not principally involve supplying a good. It is to place a bundle of capabilities and competences (human, technological, organizational) at the disposal of a client and to organize a solution which may be given to varying degrees of precision.

Providing a service could mean participating in a process innovation for another firm. Unlike process or product innovations, services require more than technical skills. Services rely mostly on social relationships and organizational capabilities to facilitate innovative activities (L.-J. Chen, Chen, & Lee, 2008; Hertog, 2000). Social relationships can then refer social proximity which is defined by R. Boschma (2005) as the trust relations between actors and they are based on friendship, kinship and experience. Social proximity is required for organizations to be able to learn and innovate because it can facilitate the exchange of tacit knowledge that is more difficult to trade through markets (Maskell & Malmberg, 1999). Social proximity is often studied in clusters because geographical proximity is not enough to explain the fostering of collaboration and innovation anymore (Letaifa & Rabeau, 2013). Services are comprised of two major types of firms: the high-tech services (Van Riel, Lemmink, & Ouwersloot, 2004), and the KIBS (Hertog, 2000). High-tech services as defined by Van Riel et al. (2004) involve the use of ICT to deliver their innovations. KIBS are firms that rely on highly specialized knowledge to provide services or products that are knowledge-based (Hertog, 2000). These firms also focus on accumulating, creating or disseminating knowledge to their clients in order to satisfy their needs (Bettencourt, Ostrom, Brown, & Roundtree, 2005). KIBS are viewed as facilitators, carriers and sources of innovation (Hertog, 2000). Services are about the experience they bring to the customer (Chesbrough, 2011) through the social relationships and the quality of the delivery. Services are intangible, heterogeneous and are co-produced with customers (Fitzsimmons & Fitzsimmons, 1999) and therefore, the OI paradigm is applicable. These characteristics affect the development process of services making them unique (Nijssen, Hillebrand, Vermeulen, & Kemp, 2006). Because services are co-produced with customers, there is no difference between the 3 different phases of the innovation cycle (James H. Love & Roper, 2004). This means that there is an interaction between new services development and its delivery (Tatikonda & Zeithaml, 2002). Finally, a new service development requires *"integrating the needs of new service operations and processes with those of existing business activities"* (Johne & Storey, 1998, p. 207). Although, Langeard, Reffait, and Eiglier (1986) considered this as a problem, it is actually an argument to use an innovation approach. In fact, there is a constant collaboration and feedback between the firm and the customers implying that the paradigm would be perfectly applicable. One of the main advantages of using OI into services is for the external search of knowledge with customers and competitors. In fact, while R&D had no effect, external sourcing increased the probability of innovating (Aija Leiponen, 2005). The diversity of innovation in services is directly related to business growth (James H. Love, Roper, & Bryson, 2011). This diversity includes marketing, strategic, and business process changes. Since services aren't standardized, they often result in a combination of knowledge and best practices from various sources, which is a positive aspect that can be attained with the new paradigm. However, this is also a challenge since protecting the knowledge becomes difficult and therefore, sharing with others can become risky. In sum, the field remains fairly new and a lot of research needs to be conducted before implying that OI is perfectly applicable.

2.2.9 Open innovation according to the industry and size of the firm

The early literature on OI studied the adoption of the paradigm in large high-tech and manufacturing firms for the most part (Chesbrough, 2003b; Laursen & Salter, 2006). Chesbrough initially studied the paradigm in high-tech companies such as IBM and Xerox. The concept has also been studied in open source successes such as Linux (Henkel, 2006) and proprietary platform vendors (Apple, IBM, Sun) (West, 2003). Later, the concept was studied in low tech and more mature industries (Chesbrough & Crowther, 2006) as well as large and medium-sized firms in multiple industries across Europe (U. Lichtenthaler & Ernst, 2007, 2009b). Many of the studies use small samples except for a study in the UK taking into account 2707 firms (Laursen & Salter, 2006). More recently, a study on the breadth and depth concept introduced by Laursen and Salter in 2006 on open eco-innovation used a final working sample of 14,366 firms (Ghisetti, Marzucchi, & Montresor, 2015). Nowadays, a lot of efforts are focussed on studying the adoption of OI in SMEs (S. Lee et al., 2010; Molina-Morales, García-Villaverde, & Parra-Requena, 2011; Narula, 2004; van de Vrande et al., 2009).

The application of OI can be affected by both the industry and the firm size. Although, OI seemed to be more adapted to the high-tech sector at first because most studies were in that industry, firm size proved to have a more notable effect on the paradigm. OI is easier to measure in large firms because unlike SMEs, they have access to more external resources and assets (Narula, 2004). SMEs will usually rely on external sources more than large firms and so as a result they focus on alliances and networks to extend their technological competences (Edwards, Delbridge, & Munday, 2005; Rothwell, 1991). Small firms would tend to use OI because they do not have the internal resources (U. Lichtenthaler, 2008b). Moreover, SMEs rely on larger firms for alliances (Rothwell & Dodgson, 1994) which means that they are already adopting some form OI through the use of external channels. According to Vanhaverbeke and Cloodt (2006), SMEs focus on external sources to help them with the commercialization stage which is not really known for OI approaches. However, SMEs remain major actors in innovation and therefore OI strategies are worth investigating (Maula, Keil, & Salmenkaita, 2006). Furthermore, SMEs and large firms are specialized in a certain type of innovation (Vossen, 1998). In other words, although the size of the firm might have an effect on innovation performance, OI is still an applicable paradigm but at different stages of the innovation cycle.

Nowadays, with Internet technologies and social networks, firms are able to collaborate with their customers, suppliers or other partners to develop a new product (Chesbrough & Prencipe, 2008), which may lead to think that the industry is not significant to the applicability of the paradigm. Although high-tech firms seemed to be the pioneers of OI in the first studies, many other industries followed. For instance, firms in electronics, semiconductors, pharmaceuticals, chemicals and automotive have been studied (U. Lichtenthaler & Ernst, 2007, 2009b). The applicability of OI is not determined by industry characteristics (U. Lichtenthaler, 2008b).

In sum, the industry doesn’t seem relevant for the application of OI but size matters. Although the OI paradigm has first been observed in large high-tech firms, it seems that most of the other industries are able to adopt this approach. Considering the size of the firm, small firms seem to be forced to look outside their boundaries because they do not have the internal resources. In this case, OI can be an advantage for them, but it can also be costly since they do not have the network to search for the right partners. On other hand, a large firm’s main advantage is its network enabling to easily look for the right partners to accelerate innovations. Large firms also have the advantage of using OI to search for smaller firms that do not have the resources and buy their technology or collaborate with them to gain a competitive advantage.

2.2.10 Summary and conclusion

In this section, the different types of innovations (i.e. product, process, organizational and marketing) were explained. The literature around the paradigm of OI that can be adopted in various industries was also reviewed. OI practices comprise many different interactions types between two actors. For example, firms can collaborate or form strategic alliances to align on common goals. The different OI practices can be applied in the form of strategic alliances, partnerships or simply collaboration. These practices can occur with different types of partners including other firms such as competitors or suppliers, universities and the government. Most of OI usage occurs in larger firms and is focussed on product development in high-tech firms. However, there is evidence that OI also has an important presence in process and service development (James H. Love et al., 2011; Nijssen et al., 2006). Industry and size also play a role. While high-tech industries adopt OI at the highest rates, other industries may find it more difficult to do so due to the need of protecting their inside knowledge. For instance, industries such as the military or aerospace will tend to be more closed than their peers. In general, larger firms can adopt OI more easily because of their large networks. SMEs have to rely on intermediaries which will help them partner with institutions or larger firms to increase their innovation potential. In other words, the adoption of OI can have an impact on innovation performance and the propensity to innovate. However, it is worth noting that the decision to collaborate with other firms will depend on a firm's absorptive capacity. Any knowledge shared must be absorbed and integrated within a firm's knowledge base to lead to increased innovation. There must be some form of complementarity with what is shared so it can be useful. Firms need to rely on interpersonal networks to interact and share knowledge, which is focused the dimension of proximity. This concept is discussed in Appendix A. The next section will discuss advanced technologies and their impact on the propensity to innovate.

2.3 ADVANCED AND EMERGING TECHNOLOGIES

According to E. M. Rogers (2010), a firm chooses technology adoption when it considers it is the best possible strategy to take advantage of innovation. In fact, this adoption changes the structure of an organization and promotes the generation of new thoughts and strategies (Bunduchi, Weisshaar, & Smart, 2011; Strüker & Gille, 2010). In other words, adopting a technology innovation brings positive changes to an organization. To that extent, many firms have chosen to adopt technologies such as Warehouse Management System (WMS) or Material Handling (MH) equipment to allow cost reduction and improve efficiency. However, regardless of the benefits provided by these technologies, companies are always looking for the next innovation that they will adopt (Reyes, 2011). Despite many studies outlining the benefits of technology, there are conflicting findings in terms of technology adoption and its effect on firm performance, which is commonly referred to as the technology paradox (Richey, Daugherty, & Roath, 2007). For example, Narayanan, Marucheck, and Handfield (2009) found inconsistent effects in the adoption of Electronic Data Interchange (EDI) in their literature review. Furthermore, most studies lack the global view of technology adoption because they normally target the effect of one technology and its impact on firm performance (Dehning, Richardson, & Zmud, 2007; Y. Wu, Cegielski, Hazen, & Hall, 2013). This study is aimed at addressing the gap by focussing on many different families of technology and try to understand in a holistic approach how they complement each other.

Moreover, to find complementarities between technologies, there must be enough firms that have adopted the same bundles of technologies. It would be logical to believe that firms seek to adopt best-in-class technologies according to the industry's best practices. In fact, there is a social and normative context in which organizations are rooted (DiMaggio & Powell, 2000). In this context, there is a need for decision makers to seek approval for their actions (Dacin, Oliver, & Roy, 2007) based on human or financial capital. For example, this can be the case when a firm is looking to adopt a new technology. Furthermore, organizations will tend to look at success stories in their networks and try to imitate them by adopting the same technologies or processes that led the firms in their network to success (Sodero, Rabinovich, & Sinha, 2013). In this case, success can be measured as an improved firm performance or an increased number of innovations. This means that the decision to adopt a technology can stem from the institutional environment in which the firms are embedded. In a literature review about EDI, it was shown that some firms feel that they must adopt EDI because other large partners in their supply chain have done so (Narayanan et al., 2009). For example, Handfield (1995) argues EDI adoption becomes a necessity to remain competition because of how popular it is in specific industries such as in retail, automotive and healthcare.

This section reviews the literature around the adoption of advanced technologies and their effect on firm performance. Four types of technologies are reviewed: material handling, supply chain and logistics, business intelligence, design and information control, and processing and fabrication. The intent of this chapter is to present an overview of technology adoption and determinants and the impact these technologies can have on firm and innovation performance. The next paragraph presents a brief review of the different frameworks regarding the assimilation of technologies, such as the resource-based view (RBV), the technology acceptance model (TAM), the innovation diffusion theory (IDT) and the absorptive capacity as was mentioned in the section on OI.

2.3.1 A condensed review of different adoption determinants

There are many different models that can explain technology adoption behaviours. This section briefly reviews the frameworks used in previous research. The concept of resource-based view (RBV) of the firm (Wernerfelt, 1984) posits that firms possessing rare and often non-substitutable resources will gain a competitive advantage in the market (J. B. Barney, 2012). Over the years, scholars have applied the RBV to analyze the effectiveness of technologies (Crook & Esper, 2014; Fawcett, Wallin, Allred, Fawcett, & Magnan, 2011). Furthermore, RBV studies started to focus more on how a firm makes use of its resources (Priem & Swink, 2012). This can be compared to a similar approach known as the practice-based view in which firms can utilize imitable practice enhance their performance (Bromiley & Rau, 2014). In this case, an “imitable practice” means that firms adopt similar bundles of technologies in order to improve their performance. It should be argued that it can be applied to any type of technology adoption.

The technology-organization-environment (TOE) framework provides a foundation for technology adoption that can be adapted due to environmental factors (L. Tornatzky & Fleischer, 1990). In the case of SCT specifically, TOE can influence their implementation based on three contextual variables: industrial, competitive and regulatory. This framework can be related to the institutional environmental context whereby industrial (normative), competitive (mimetic), and regulatory (coercive) forces could influence the implementation of SCT (Zhu & Kraemer, 2005; Zhu, Kraemer, & Xu, 2006).

The technology acceptance model (TAM) is another theoretical model that explains the motivation of users to adopt and use a technology (F. D. Davis et al., 1989). It is mostly applied at the individual level. There two factors that can influence a user to adopt a technology: (1) how useful the user perceives the technology, (2) how easy it is to use. On the other hand, the adoption rate of innovations at an organizational level can be explained by the innovation diffusion theory (IDT) introduced by Rogers in the early 1960s (E. M. Rogers, 1962). According to IDT, there are five innovation attributes that can impact an innovation's adoption rate (in this case, an advanced technology) including relative advantage, compatibility and complexity. Many studies have used TAM and IDT to understand adoption behaviour for different types of technologies ranging from consumer adoption of mobile payments to RFID adoption in supply chains (Mallat, 2007; Y.-M. Wang, Wang, & Yang, 2010). Another important approach regarding adoption determinants is the contingency theory (CT) as described by Donaldson (2001). In fact, CT allows firms to be efficient by finding the right elements that fit to its characteristics. According to Ungan (2004), CT is one model that can influence a firm's decision to adopt specific technologies. Finally, absorptive capacity (AC) is a firm's ability to assimilate and utilize new knowledge received from external partners (e.g., suppliers, customers) (W. M. Cohen & Levinthal, 1990; Malhotra, Gosain, & Omar, 2005; Zahra & George, 2002). In other words, firms will choose which technologies to adopt based on which technology seems to fit best according to their current knowledge level. Taken from an OI perspective, AC is the ability of a firm to absorb external knowledge, which in this case represents a new technology.

Based on these findings, the research can start to be elaborated by looking at the theoretical frameworks, in particular RBV, IDT, absorptive capacity and CT. Specifically, CT and IDT have been used in previous studies as adoption factors in supply chain and manufacturing technologies (Oettmeier, Oettmeier, Hofmann, & Hofmann, 2017; Ungan, 2004). AC has also been used as a mediating factor in technology adoption (H. Liu, Ke, Wei, & Hua, 2013), which is why it is included as a theoretical background for this study. Because TAM is mainly used at the individual level, it is not relevant for this research. In fact, whether individual users have decided to fully adopt a technology or not can't be measured because the survey used is at the firm level. As will be presented in the following section, complementarities between technology adoption are of interest. There are potentially three groups of factors that can influence the adoption rate: (1) technology-related factors based on the benefits a technology can bring, (2) firm-related factors based on absorptive capacity and complementarity, and (3) context-related factors based on external pressure from partners and outside support. Based on these three factors, it can be expected to find patterns and complementarities in technology adoption amongst firms.

Finally, another important concept to focus on in this research is technological complementarity, which is defined as "unique and symmetric strategic combination of firm roles, goals, readiness for the implementation and use of technology across partnering firms and the extended supply chain" (Richey et al., 2007, p. 198). Knowledge exchange between a firm and its suppliers can increase product innovation performance (E. Thomas, 2013). In terms of technologies, the different actors of the supply chain are expected to have similar bundles of technologies adopted. Having similar resources can facilitate collaboration and integration with suppliers, which will result in achieving supply chain innovation goals (Flynn, Huo, & Zhao, 2010). It is also logical to believe that some bundles will be specific and unique depending on the firm's characteristics (e.g. industry, size, capital expenditures). Although a firm or its partners can't be identified in the survey used, it is possible to identify the most adopted bundles and try to find patterns of adoption. According to T.-L. Liu and Shou (2004), a high resource complementarity between firms can result in benefits from strategic alliances and an increased operational performance point of view. Operational efficiency can also be optimized when there is a technological match (Tosi Jr & Slocum Jr, 1984). In contrast, low complementarity can lead to increased costs and the reduction of long-term cooperation (T.-L. Liu & Shou, 2004). Suppliers that are involved in the innovation process can make supply chains more flexible to customers' demands (Jajja, Kannan, Brah, & Hassan, 2016). Companies will constantly try to be aligned with their partners to facilitate their integration within the supply chain (Yang, Rui, Rauniar, Ikem, & Xie, 2013). This is true for technologies used across the supply chain. In fact, technological proximity has been linked to innovation (Huber, 2012). Furthermore, long-term goals that are shared between companies and their suppliers result in more innovation (Pulles, Schiele, Veldman, & Hüttinger, 2016). For these reasons, this research is focussed on finding and understanding the common bundles of technologies that firms adopt.

2.3.2 Advanced material handling/supply chain technologies (SCT)

Some studies in the literature have been focussing on understanding the effects of SCT adoption (H. Liu, Ke, Wei, Gu, & Chen, 2010; Saeed, Abdinnour, Lengnick-Hall, & Lengnick-Hall, 2010). There have been many drivers that can influence technology adoption such as factors related to the technology itself (i.e., benefits, complexity and compatibility), the organization (i.e., structure, size) and the environment of the firm (i.e., market competition, influence from suppliers) (Lai, Wong, & Cheng, 2006; Sodero et al., 2013). Studies have shown that information sharing between all the supply chain partners is a good indicator of how effective SCT technology will turn out to be (Sanders, 2005; Ye & Wang, 2013). This could indicate that OI facilitates the adoption or the successful utilization of technologies.

When it comes to Supply Chain Technologies (SCT), many firms rely on them to gain a competitive advantage and create value for shareholders (Mishra, Modi, & Animesh, 2013; Yao, Dresner, & Palmer, 2009). These technologies may also be implemented to increase communication and integration of the supply chain actors (Autry, Grawe, Daugherty, & Richey, 2010). Many studies have focussed on SCT adoption (H. Liu et al., 2010) and utilization (Z. Liu, Prajogo, & Oke, 2016; Narayanan et al., 2009). Z. Liu et al. (2016) make the distinction between adoption and utilization in the sense that managers may be resistant to utilizing a technology even if it has been adopted. In fact, there is some evidence that such technologies are not always used to their full potential (J. Lee, Palekar, & Qualls, 2011) and that supply chain managers can manifest resistance to change (K. A. Patterson, Grimm, & Corsi, 2004; Saldanha, Mello, Knemeyer, & Vijayaraghavan, 2015). If a firm adopted a Transportation Management System (TMS) recently to track all transportation in their warehouses but that its employees are still using spreadsheets instead from time to time, the benefits of a TMS adoption will not be as expected. Although utilization at the individual level is not measured in this study, it is assumed that a firm that is adopting SCT to be planning to fully use it.

Furthermore, an increasing market competition is pressuring firms to adopt SCT to benefit from decreased operation costs by increasing their capital available through better inventory management (Mishra et al., 2013). More capital leads to more investment opportunities that can result in a gain of competitive advantage (Oh, Teo, & Sambamurthy, 2012). Many technologies allow firms to be more efficient in their supply chain operations (Devaraj, Ow, & Kohli, 2013). For example, recent studies have shown that customer relationship management tool (CRM) is typically used to target the most profitable customers as well as increasing profits from the less profitable ones (Rababah, Mohd, & Ibrahim, 2011; Y. Wang & Feng, 2012). Similarly, Warehouse Management Systems (WMS) are typically adopted to optimize space, personnel and even material handling equipment, which results in better productivity (K. A. Patterson et al., 2004). Furthermore, these two tools can be typically integrated with an Enterprise Resource Planning (ERP) software. It has been shown that ERP contributes to improving inventory control (Hendricks, Singhal, & Stratman, 2007) which results in better cost control strategies for the supply chain (Mishra et al., 2013).

One of the central and most adopted technologies in SCT is a CRM tool. The concept of CRM isn't just to describe a software but consists of set of strategies and philosophies that provide a firm with the right tools to manage their customers' transactions (Peters, Pressey, & Greenberg, 2010). Information about customers should be used to create effective marketing strategies that target the most profitable customers (Bradshaw & Brash, 2001; Rababah et al., 2011). Studies have shown the multiple benefits of adopting CRM related to improving customer satisfaction (Karjaluoto, Ulkuniemi, Wongsansukcharoen, Trimetsoontorn, & Fongsuwan, 2015; Kasim & Minai, 2009). It has been demonstrated that CRM tools can have a positive impact on customer knowledge and customer satisfaction (Mithas, Krishnan, & Fornell, 2005). These benefits have resulted in increased business performance and business profits for firms (Daghfous & Barkhi, 2009; Y. Lin & Su, 2003; Lo, Stalcup, & Lee, 2010). Therefore, adopting a CRM will increase a firm's overall performance. However, for firms that do not have the capital to invest in a CRM, these benefits can be achieved by improving communication and processes with customers (Pan, Tan, & Lim, 2006).

Regardless of these technological factors, some organizational factors come into play when deciding whether to adopt advanced SCT or not. For example, large organizations will have enough financial resources to test a technology before implementing it at full scale. In addition to that, they have enough resources to help their supply chain partners go in the same direction (Mabert, Soni, & Venkataramanan, 2003). Furthermore, technical “know-how” in an organization is a good indicator and motivator to adopt new technologies (Sulaiman, Umar, Tang, & Fatchurrohman, 2012). In fact, firms with more knowledge tend to assess the advantages and disadvantages of technology adoption. This will result in firms executing a technology adoption strategy (Roh, Kunnathur, & Tarafdar, 2009). External partners can also influence the adoption of a new technology. According to Roh et al. (2009), firms can be influenced or pressured to adopt because of governmental incentives or a competitive ecosystem.

2.3.3 Advanced Business Intelligence and Analytics technologies

The adoption of advanced business intelligence technologies and analytics (BI&A) has been widely spread across different industries in recent years. These technologies represent a set of tools and applications with the purpose of collecting, storing and analyzing data to improve decision-making (Namvar, 2016; Wixom & Watson, 2010) A recent industry report by Gartner (2007) forecasted that the BI&A market will reach $22.8 billion by 2020. Companies continue to invest heavily in these technologies because it helps them understand customer needs and quickly adapt to changes perceived with data collection, which can result in an increased performance and competitive advantage (Park, El Sawy, & Fiss, 2017; Torres, Sidorova, & Jones, 2018). Despite the increasing investments in BI&A, some scholars believe that it is difficult to measure their return on investment (Popovič, Turk, & Jaklič, 2010; Yeoh & Popovič, 2016) due to a lack of common success criteria. In fact, it’s difficult to evaluate the investments in BI&A technologies because their benefits remain intangible (Dobrev & Hart, 2015). As a consequence, adopting these technologies remains a challenge because it implies gathering stakeholder’s support for benefits that could take a lot of time and adjustments to be seen (Hughes, Dwivedi, Simintiras, & Rana, 2016; Yeoh & Popovič, 2016).

However, it can be argued that BI&A technologies increase a firm’s propensity to innovate. As described by Bantau and Rayburn (2016), the first and second wave of ICT were used to automate individual activities and increase connectivity respectively. Today, advanced technologies that are often ICT-driven have become part of complex products and play a key role in productivity improvement (Breur, 2015; M. E. Porter & Heppelmann, 2014). Advanced BI&A technologies and connectivity provide new data and a potential competitive advantage to organizations able to make use of it (M. E. Porter & Heppelmann, 2015). As a consequence, this data becomes usable as soon as it is generated (Van Auken, 2015). All this information generated can be used to foster great relationships with a firm and its customers. Dynamic interactions between a firm and its customers allow a firm to build relationships that provide the opportunity to adapt its services to the customer’s need (Bantau & Rayburn, 2016; Kumar et al., 2013). According to Rust and Huang (2014), this becomes very useful in consumer-centric organizations as data is collected and analyzed frequently so that the firm can provide its customers with a personalized service. Through a feedback loop, firms continuously adapt to their customers to ensure their retention. In fact, the priority becomes on their retention instead of attracting new ones (Rust & Huang, 2014). The accessibility of a customer’s data has become ubiquitous and easier to collect because of digitalization of technologies (Huang & Rust, 2013; Leventhal & Langdell, 2013). Traditionally, building relationships with customers or partners could be face to face or on the phone. Today, communication can occur with anyone willing to listen through diverse communication platforms (Wirtz et al., 2013).

All the data collected to enhance a firm’s decision-making can be labelled as big data. This term refers to large volumes of data coming from different sources and that cannot be processed traditionally because it is usually in real-time (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012). The term big data is confused with predictive analytics and the Internet of Things (IoT) which represents different methods of data collection and analytics that can be transformed into knowledge to enhance fact-based decision-making (Bose, 2009; Shariat & Hightower Jr, 2007). Big data capabilities consist of three main sources of data: traditional data including focus groups and transactions, digital data including social media platforms and blogs, and firm specific data that can include data from products, services offered or metrics (Kumar et al., 2013; M. E. Porter & Heppelmann, 2015; Weinberg, Davis, & Berger, 2013). Big data collected with a big data software (BDS) will lead to big data analytics (BDA) which can enable many improvement possibilities. BDA and artificial intelligence (AI) will be briefly discussed later in section 2.3.6.

One of the most prolific innovations in BI&A technologies is Software-As-A-Service (SaaS) or cloud computing (CC). SaaS allows businesses to use applications remotely, not only for BI&A software but also for the other types of technologies that were previously mentioned (e.g. CRM, TMS, ERP, WMS). Like all other BI&A technologies, the SaaS literature discussed many benefits that can be divided into two categories, namely operational (e.g. cost reduction and support in business operations) and new improvements (e.g. process, product and service) (Benlian & Hess, 2011; Marston, Li, Bandyopadhyay, Zhang, & Ghalsasi, 2011; Rodrigues, Ruivo, & Oliveira, 2014; Venters & Whitley, 2012). Some of these benefits will be presented in Chapter 3. Despite the many benefits in a firm's business processes, there are not many studies regarding a firm's innovation performance due to SaaS adoption. A study from 243 firms in the USA concluded that the adoption of SaaS resulted in increased impact in terms of ICT-enabled innovations whether it was pertaining to product, process or service innovations (Malladi & Krishnan, 2012). Using a similar methodology, Schniederjans and Hales (2016) also found a positive impact on a firm's economic performance as a consequence of SaaS adoption. Furthermore, they also found that CC increases supply chain collaboration, which results in an increase in firm performance. SaaS can be expected to increase collaboration because the service can be accessed on the Internet. Advanced manufacturing technologies are discussed next.

2.3.4 Advanced manufacturing technologies (AMTs)

Many studies discuss the adoption of technologies applied to operations management in the literature (Khanchanapong et al., 2014; Kotha & Swamidass, 2000; Swink & Nair, 2007; Uwizeyemungu, Poba-Nzaou, & St-Pierre, 2015). In manufacturing, technology is defined as the set of tools including automation and integration, used in the different stages of design, manufacturing, planning and control of the product (Ettlie & Reifeis, 1987). However, the literature provides no consensus on how to categorize the different types of technologies used in manufacturing industries. Most studies refer to advanced manufacturing technologies (AMTs) (Boyer, Leong, Ward, & Krajewski, 1997; Fulton & Hon, 2010; Khanchanapong et al., 2014; Uwizeyemungu et al., 2015), while some other scholars refer only to MTs (Nair, Ataseven, & Swamidass, 2013). The difference between AMTs and MTs may come from the fact that empirical studies are unable to measure whether technologies are advanced or not (Bello-Pintado, García Marco, & Zouaghi, 2018). For example, in the survey used in this research, it is known that a firm has adopted an Enterprise Resource Planning (ERP) tool or Computer-Aided Design (CAD) system, but not which version it is using, the type of software adopted or if the technology is frequently updated. However, this study will continue to refer to these technologies as AMT in the remainder of this review. AMTs include design and information control technologies, and processing and fabrication technologies. Besides the definition available in the survey, another way to categorize AMTs is to divide them into three families: technologies of production design (e.g. computer-aided design, engineering and process planning); technologies of manufacturing processes (e.g. numerically controlled machinery and robots); and technologies of administrative production (e.g. material requirement planning (MRP) and ERP) (Boyer, Ward, & Leong, 1996). On the other hand, Nair et al. (2013) refer to soft technologies (ERP, MRP and other planning tools) and hard technologies (robots, Computer-Aided Engineering (CAE)). The next chapter will be defining each technology. As was previously mentioned, the study of the complementarity between each family of technology is of interest. According to Bello-Pintado et al. (2018), this idea of complementary set of technologies may have an effect on firm performance.

Many studies back the idea of AMTs having a positive effect on firm performance. In fact, the specific combination of a set of AMTs in a firm can make it difficult to be transferable by another firm and thus, provides a competitive advantage (Milgrom & Roberts, 1995; Stoneman & Kwon, 1994). This is a direct consequence of the RBV theory that discusses how to achieve a sustainable competitive advantage that is not easily imitated (J. Barney, 1991; Hamel & Prahalad, 1994). According to Gómez and Vargas (2012), these complementarities can break silos between the different departments because they allow to build integrated systems. However, it is important to stress that the literature showed mixed outcomes relative to capital expenditures in these technologies. Some authors discuss that investments in AMTs can improve a firm’s performance (Cozzarin, 2016; Dean Jr & Snell, 1996; Gordon & S. Sohal, 2001) while others do not find similar results due to failure of introducing AMTs (Boyer et al., 1997; Koc & Bozdag, 2009). These failures may be due to a misalignment between AMTs and a firm’s business strategies or an unsuitable technology for the production to be addressed (Fulton & Hon, 2010; Iakymenko, Alfnes, & Thomassen, 2016). Percival (2009) discusses potential interactions of technology adoption with other factors as manufacturing firms continually spend on new technologies despite the risk of failure. Khanchanapong et al. (2014) suggest that lean practices might have an effect on the outcomes of AMTs while some other authors discuss human resources strategies as a possible contributor (Cagliano & Spina, 2000; Swink & Nair, 2007).

Furthermore, the effect of advanced technology adoption on firm performance seems to be conflicted in the literature (Bülbül, Ömürbek, Paksoy, & Bektaş, 2013; Koc & Bozdag, 2009). For example, H. Zhou, Leong, Jonsson, and Sum (2009) found a positive correlation of AMTs' capital expenditures and firm performance in Swedish firms but it wasn’t the case in Singapore. Birdi et al. (2008) did not find any statistically significant relationship between AMTs and productivity when comparing the data collected from 308 firms over 22 years. Furthermore, some scholars found that the implementation of AMTs will most often result in a failure (Koc & Bozdag, 2009).

Although the effect of AMT on performance is complex, studies show different types of relationships. For example, some studies show that factors, such as operations improvement and quality management practices can mediate the AMT-performance relationship (Choe, 2004; M. G. Patterson, West, & Wall, 2004), while other scholars show that it can be moderated by these same factors (Laosirihongthong & Paul, 2004; Lewis & Boyer, 2002; Q. Zhang, Vonderembse, & Cao, 2006). In addition to these factors, the RBV theory states that AMT requires complementary resources and capital expenditures to improve their performance. Fulton and Hon (2010) found that AMT needs investment in training and mentoring while other studies stress the importance of developing good relationships with suppliers (Abd Rahman & Bennett, 2009; Rahman, Brookes, & Bennett, 2009). Ghani, Jayabalan, and Sugumar (2002) mention that the firm’s organization needs be adapted to the new advanced technology realities. In fact, they found that Indian manufacturing firms had very little productivity gains because of its organization structure that hasn’t evolved. All these factors become crucial for AMT adoption to be successful. Furthermore, to be successful, these AMTs require implementation efforts and a firm’s alignment strategies (Lewis & Boyer, 2002; M. H. Small, 2007). The adaptation on strategies based on the different types of AMT has proved to have a positive effect on performance (Kotha & Swamidass, 2000). Diaz, Machuca, and Álvarez-Gil (2003) identified three patterns of AMT adoption that they labelled as traditionalists, designers and investors but they were unable to differentiate between their respective performance levels. However, other studies were able to find differences in performances based on the different adoption patterns (Bülbül et al., 2013; W. Chung & Swink, 2009).

An example of a central technology to AMTs is additive manufacturing (AM), also known as 3D printing. However, 3D printing is not a single technology in AM. In fact, AM can use different materials (e.g. plastic, metals or others) to provide a different level of quality to products (Ford, Mortara, & Minshall, 2015). 3D printing can drive radical changes in manufacturing firms (Ortt, 2016). This type of technology is not new. It has been used for over 30 years but is only starting to get more popularity nowadays. Therefore, it is only recently that academic research has started to emerge as well (Ortt, 2016). Like traditional AMTs, AM has benefits that can achieve flexibility and complexity (Weller, Kleer, & Piller, 2015). Niaki and Nonino (2017) emphasize on the economic benefits of AM due to flexibility and inventory turnover decrease which is promoted by on-demand customer customization. Some technologies can even enhance productivity when doing manufacturing at a large-scale (Ituarte, Khajavi, & Partanen, 2016), which can increase firm performance in return. Furthermore, the propensity to introduce process and product innovations may be increased as a consequence of AM adoption (Niaki & Nonino, 2017). In fact, AM can help organizations reach new customers and even develop new products that were not possible with other AMT (Mellor, Hao, & Zhang, 2014; Niaki & Nonino, 2017).

2.3.5 Emerging technologies (Internet of Things)

The Internet of Things (IoT) is the next step for many firms as it is a big leap towards Industry 4.0. IoT connects so many devices that there aren’t enough people use them individually (Gubbi, Buyya, Marusic, & Palaniswami, 2013). Many studies mention the IoT as an interconnection of devices through the Internet and cloud computing that results in a network of devices sharing information (Bantau & Rayburn, 2016; Gubbi et al., 2013; Kortuem, Kawsar, Sundramoorthy, & Fitton, 2010; M. E. Porter & Heppelmann, 2014, 2015). In other words, IoT technologies process and analyze data that can be fetched from sensors and databases in real-time (Gubbi et al., 2013). The result is then outputted so an action can be taken by another device or a human. According to M. E. Porter and Heppelmann (2014), these technologies have more main functions: (1) monitoring, (2) control, (3) optimization, and (4) autonomy. To produce these capabilities, IoT is built on an integration of physical sensors, middleware applications and, of course, connectivity (Gubbi et al., 2013; M. E. Porter & Heppelmann, 2015). Gubbi et al. (2013) describe the interaction between these three enabling technologies. Physical sensors can be either embedded in products or used as stand-alone sensors. They require Internet connectivity as well as some a software that will allow an interaction with other connected devices. The last component is connectivity that ensures the devices are connected so they can exchange data in real-time. Different network technologies can be used to allow connectivity between the multiple devices, Wi-Fi, RFID and Bluetooth being just a few of the options. The whole process is also supported by middleware applications. The main use of this technology resides in the manufacturing sector to optimize performance of integrated machines and equipment (Gubbi et al., 2013; M. E. Porter & Heppelmann, 2014). One of the prime examples used in the early stages of IoT is automatic tracking of products through RFID applied to supply chains. Apple Pay is another example used another IoT technology known as NFC. A few years ago, geotagging capabilities were introduced allowing to signal their location ("check-in") to places they visit (Higginbotham, 2015). Other applications include providing good customer service by detecting a problem before the customer calls. As such, aggregated information can be available on repeated similar problems that will prompt a firm to innovate to eliminate or reduce issues to improve customer experience (Bantau & Rayburn, 2016). IoT integration enables big data collected from multiple sources that can be analyzed to predict issues as opposed to reacting to them. This allows for better service repair optimization and recovery (M. E. Porter & Heppelmann, 2015).

As previously mentioned, RFID is one of the main technologies required for IoT implementation. RFID is a tracking and tracing system that allows companies to quickly retrieve information on materials or products stored in their warehouses. Due to the popularity of QR/Bar coding, it may be perceived as a technology that is complicated to implement. In fact, the higher the complexity of adopting a new technology, the higher the resistance to change that may manifest. While RFID is no longer an emerging technology, firms could decide to defer its adoption if it is evaluated as too complex (L. G. Tornatzky & Klein, 1982). There are many benefits to adopting RFID technology. First, it can increase the visibility of the supply chain not only for the firm adopting it but for its partners as well (Angeles, 2005). Therefore, this results in increased data accuracy and more information sharing about the tracking and tracing of materials (Angeles, 2005). Because materials are easier to track, RFID can also increase efficiency of material handling and inspection time (L. G. Tornatzky & Klein, 1982). Studies found that multiple other benefits such as decreased human errors in manual data entry about product information and its location (Spekman & Sweeney, 2006). In fact, these tasks are automated with RFID as data on the product and its location are directly stored in a database. This data can be easily shared with suppliers and other actors in the supply chain if the products are tagged with a chip (Twist, 2005; Zaltman, Duncan, & Holbek, 1984). It is estimated that the time to count inventory is reduced by 40% when RFID is implemented (Quirk & Borrello, 2005). One of the reasons for the reduced time is because RFID allows multiple items to be scanned at the same time, which results in costs savings (Zaltman et al., 1984). In this sense, RFID can be considered an upgrade compared to QR or barcode because it doesn’t need an alignment or specific orientation between the scanner and the tag (Bunduchi et al., 2011).

Despite the many advantages of RFID, there are different kinds of obstacles that may prevent firms from adopting them. One of the most important reasons is the upfront costs needed. Unlike QR or barcodes, RFID codes are repetitive cost. The tags will also generate a lot of data that need the infrastructure to be dealt with. This can lead to extra costs that can prevent a firm from adopting the technology. In fact, tags require printers and scanners as well as extra IT systems to deal with the large amount of data that will be generated (Attaran, 2007). Another important barrier to RFID adoption is the popularity and inexpensive price of barcodes. Twist (2005) argues that more than 5 trillion barcodes are printed yearly because they are cheap, standardized and already procuring benefits to firm performance. Due to their popularity, firms are dependent on barcodes have reached a comfort zone, which is not helping in the adoption of RFID (Kang & Gershwin, 2005). Considering the other obstacles to adoption that were previously mentioned, adopting a new technology, while the one currently implemented is working, can create an environment of uncertainty. In the case of RFID, this uncertainty can affect the adoption rate (Cannon, Reyes, Frazier, & Prater, 2008). Other setbacks to adoption include privacy and security concerns (Srivastava, 2004) and accuracy issues when tags are in close proximity together (Venkatesh, Morris, Davis, & Davis, 2003). For these reasons, RFID is not expected to have a high adoption.

2.3.6 Artificial Intelligence (AI)

Artificial Intelligence (AI) is a technology that has the power the impact all industries. AI is considered an extension of BI&A technologies as it requires a Big Data software (BDS) to do big data analytics (BDA). According to Hof (2015), AI is a mechanized device that can interact with its environment based on deep learning, a digital representation of the millions of neurons in the brain. However, AI not necessarily need to interact with its environment. For example, using machine-learning algorithms to perform predictive analytics is a technique that has already been widespread in companies. Incorporating AI into analytics means a system can make assumptions and learn automatically from data. With data collected in real-time, the next step for an algorithm or a robot is to react intelligently to an external stimulus. A great example of early AI is digital assistants. Although they still do not have the full problem-solving potential of humans, they are becoming more and more popular with a lot of different abilities. Most of these technologies are passive and react to a user's input (Bantau & Rayburn, 2016). However, today's artificial intelligence is going further than that. According to Wirtz and Lovelock (2016), robots are now being used for check-in and room cleaning services in some hotels. Some digital assistants can now make a call and interact with a human to take an appointment or reserve a table at a restaurant. While we are on the edge of self-driving cars, John Deere has been offering autonomous tractors to farmers for years (Peterson, 2015). All these technologies will continue to play an important role in productivity gains across different industries.

To be able to adopt AI in a way, BDA is a necessity because it allows for complex algorithms to be implemented. The early literature on BDA has shown a positive relationship between the use of big data analytics and firm performance in the retail industry (Germann, Lilien, Fiedler, & Kraus, 2014). This type of analytics is quickly becoming an important aspect to guide businesses in their decision-making process (Hagel, 2015). According to a study by Y. Liu (2014), BDA can help increases a firm's revenue by 8%. For example, about 35% of online sales on Amazon are generated from providing personalized purchases recommendations to customers (Wills, 2014). The importance of AI will continue to grow over the years as more and more algorithms are being deployed to understand customer behaviour and guide decision-making. To have many different technologies to choose from means that there are many sources of data to connect to and from which AI can learn and provide even more business value.

2.3.7 Complementarities between technologies

Firms adopt technologies based on their complementarities with their current processes (Zmud, 1984). There are two models that have been used to explain the progression of AMT adoption by firms: the incremental and the discontinuous models (Boyer, 1999). According to the incremental model, new technologies are adopted in a sequential order once the previous are fully implemented and successful (Meredith & Hill, 1987). On the other hand, the discontinuous model supports the adoption of an integrated suite of technologies (Meredith & Hill, 1987). Therefore, it is logical to believe that firms will adopt specific bundles or technologies at different times. In fact, firms do not adopt one technology but rather a group of technologies sequentially or incrementally (Gómez & Vargas, 2012). The analysis tackles both angles because it focusses on popular bundles adopted with and without considering the time of adoption. In the incremental model, there is the process of learning-by-using which means that firms may learn from using previous technologies (Rosenberg, 1972), which will affect their decisions when adopting future technologies. In fact, this benefit was highlighted in the Italian metalworking industry where firms reported an effect of incremental learning due to AMT adoption (Colombo & Mosconi, 1995). Other scholars also reported a learning-by-using effect from the adoption of older manufacturing technologies by Swiss companies (Arvanitis & Hollenstein, 2001) and computer technology by Californian farmers (McWilliams & Zilbermanfr, 1996). Some studies highlighted the importance of technology complementarity, but focussed on a very small number of technologies. For example, Bourke and Roper (2016) looked at complementarities in AMT for 4 technologies: Computer-Aided-Manufacturing (CAM), Material Handling (MH) technologies, Computer Integrated Manufacturing (CIM) and robots. However, the survey contains 24 different types of AMT and more than 40 technologies across all categories. To the best of our knowledge, exploring the different bundles of technologies across all different categories and industries has not been done before. From the innovation literature, scholars have discussed the benefits of complementarity innovation performance in human resources management (Laursen & Foss, 2003) and organizational practices (Lhuillery, 2000). Therefore, complementarities within the different technologies could potentially increase the propensity to innovate.

2.3.8 Summary and conclusion

This section first reviewed the different frameworks around technology adoption. It was discussed that RBV posits that firms may gain a competitive advantage due to their resources. The adoption rate of an innovation (or in this case, technologies) can be defined by certain attributes related to the IDT, such as having a competitive advantage or by its relative degree of complexity. Whether a firm decides to adopt a new technology or not can also be explained but this firm’s AC. AC is what will provide firms the ability to integrate knowledges from their partners. Technology adoption has multiple benefits from productivity increase, to cost reduction and a better propensity to innovate. Clearly, some complementarities may exist between different technologies that may be due to a firm’s AC or the pressure from external partners. For example, firms will tend to look at success stories in their networks and try to imitate them by adopting the same technologies (Sodero et al., 2013). Furthermore, according to CT, firms will tend to look for elements or technologies that fit with their core attributes. This can lead to certain bundles of technologies that will be similar between different firms, but also to bundle very specific to a firm based on its industry and core activities.

The different families of technologies that firms can decide to adopt and their impact on innovation performance were then reviewed. For instance, it was discussed that SCT, BI&A and AMT can have a positive effect on a firm’s performance by bringing a competitive advantage. Emerging technologies were briefly explored, including IoT and AI and how they can completely transform a firm. The literature around emerging technologies helped to understand which advanced technologies are prerequisites for their adoption. In fact, technologies such as RFID and BDS are very important and their adoption rate can provide insight on the emerging technologies that may be potentially adopted in the future for these firms. In Chapter 3, the role of each technology alongside a brief history about its evolution will be presented.

Finally, the complementarity of these technologies has also been explored. As was previously mentioned, there are mainly two models explaining technology adoption. The first one, the incremental model, there is a process of learning by using, which will guide firms towards their next adoption. The second one, the discontinuous model, supports the idea of adopting an integrate suite of technologies, such as an ERP. While some studies have highlighted complementarity using both models, most of them focus on a few specific technologies. To the best of our knowledge, there is nothing in the literature looking at technology adoption exhaustively across different categories. Both models, incremental and discontinuous, allow to view complementarity from a different perspective. The incremental model supports sequential adoption, allowing to understand which technologies have been adopted first, while the discontinuous model is independent of the chronology of adoption.

2.4 General synthesis of the literature review

This chapter reviewed the definition of innovation and its different types, namely technical (e.g. product and process) and non-technical innovations (e.g. marketing and organizational) and the different practices that could lead to increase a firm's innovation performance. Taking into account people, ideas and new technologies, a firm can then conduct research that will lead to new or improved products, processes, services, etc. These innovations coupled with business strategies can lead to outcomes that increase a firm's performance. While a firm can innovate on its own, Chesbrough introduced the concept of OI in 2003 to explain that firm are engaged into collaboration to accelerate and improve innovation. OI can take many forms that are classified into two categories: inbound and outbound. Firms can also adopt a coupled process which consists of sharing knowledge from inside and outside. Many types of interactions between firms can allow for information transfer ranging from cooperation to collaboration and strategic alliances. These practices can occur differently based on the sources from where it comes. For instance, collaboration with a supplier is easier as there is no direct competition. A strategic alliance might be profitable when it comes to competitors as intellectual property can be protected.

While larger firms may have access to more resources to adopt an OI model, SMEs can also use this type of practice. They may require an intermediary or be part of a cluster, which provides access to network where firms can be built interpersonal relationships. These relationships can be described by the different dimensions of proximity that were mentioned in this chapter. As a general rule, there is a proximity paradox in which firms need to be close to be able to absorb information but not too close to avoid hindering innovation. In fact, there needs to be an optimal distance so a firm can integrate homogenous and complementary knowledge. Furthermore, the concept of technological proximity was discussed, which is crucial in the Industry 4.0 era. When firms adopt many technologies as inputs to improve their innovation propensity, it is expected that they will follow best practices in the market.

To understand how these technologies can affect the propensity to innovate, the literature was surveyed to elaborate an exhaustive review of three main categories, namely SCT, BI&A and AMT. It was also mentioned some of these technologies can lead to emerging technologies such as IoT and AI. Firms adopt new tools to improve their performance, either by reducing costs, improving quality, or accelerating their manufacturing process. Adoption is usually done following specific frameworks such as RBV or AC that can give a competitive advantage and the capacity to absorb knowledge from outside sources respectively. Companies are looking to adopt technologies as a strategy to gain a competitive advantage and improve their propensity to innovate, which is the focus of this research.

This literature review contributed to identify two possible gaps that this study will attempt to fill. First, there are many papers that evaluate how open innovation and technology adoption impact innovation propensity separately. This research will aim at exploring these two factors in the same model and see their influence on a firm’s ability to introduce new products and business processes. The second potential gap that was identified is related to complementarities between each technology. Before presenting the methodology and what is being measured, the next chapter explains the details of each of the 37 technologies that are part of this study, including a brief presentation of their functionality and their evolution in time. This will allow the reader to understand which technologies may have complementary functionalities from a practical standpoint, which will be useful in proposing which technologies will be adopted together. These propositions can facilitate the interpretation of the results in Chapter 6. For these reasons, the next Chapter (Chapter 3) will be a frame of reference to better fill the gap around technology complementarity and the order in which they are adopted, leading to I4.0.

CHAPTER 3 EVOLUTION AND APPLICATIONS OF ADVANCED AND EMERGING TECHNOLOGIES

Although advanced and emerging technologies are sometimes used interchangeably, there are some important distinctions to make. The Survey of Advanced Technology (SAT) 2014 defines an advanced technology as follows:

> new technology that performs a new function or improves some function significantly better than other commonly used technology.

In contrast, emerging is not defined in the survey. Some definitions of emerging technologies focus on the potential impact they can have on the economy (A. L. Porter, Roessner, Jin, & Newman, 2002), while others argue that what defines them are the novelty and growth elements (H. Small, Boyack, & Klavans, 2014) or the uncertainty brought by the emergence process (Boon & Moors, 2008). In fact, in SAT 2014 the different types of advanced technologies include biotechnologies and nanotechnologies, which tend to have some uncertainty of how they can impact society. According to Rotolo, Hicks, and Martin (2015), an emerging technology can be defined as follows:

> a radically novel and relatively fast-growing technology characterized by a certain degree of coherence persisting over time and with the potential to exert a considerable impact on the socioeconomic domain(s) which is observed in terms of the composition of actors, institutions and patterns of interactions amongst those along with the associated knowledge production processes. Its most prominent impact, however, lies in the future and so in the emergence phase is still somewhat uncertain and ambiguous.

For example, it was previously mentioned RFID that is a required technology for enabling IoT. Although, IoT is somewhat possible today, it is considered an emerging technology principally because of its uncertainty factors. In fact, IoT has a lot of potential benefits in many areas such as logistics and navigation as well as in manufacturing. The health and fitness industries are also set to be an important market when IoT becomes widespread. On the other hand, RFID can be used right now to track equipment and, although it's not used to its full potential, can be considered as an advanced technology.

This chapter reviews the brief history of each of the advanced and emerging technologies that are being studied in this dissertation. The way these technologies work and their potential applications are explained. The Survey of Advanced Technologies (SAT) 2014 surveys firms on four main categories of technologies that are explored in this dissertation. These technologies can be found in Table 3.1.

Table 3.1: List of technologies grouped by category in SAT 2014

Material handling, supply chain and logistics (MHSCL)
a) Customer Relationship Management (CRM) software b) Software for demand forecasting or demand planning (DF) c) Transportation management system (TMS) d) Warehouse Management System (WMS) e) Supply chain collaboration and visibility systems (SCCVS) f) Automated Storage (AS) and Retrieval System (RS) g) Automated products and parts identification (e.g., bar or QR coding) h) Radio frequency identification (RFID)
Business intelligence (BI)
a) Executive dashboards for data analytics and decision-making (ED) b) Software for large-scale data processing (BDS; e.g., Hadoop) c) Live-stream processing technology or real-time monitoring (RTM) d) Software as a service (SaaS) and cloud computing software e) Infrastructure as a service (IaaS) and cloud computing hardware
Design and information control (DIC)
a) Virtual Product Development or modelling software including Computer Aided Design (CAD) Computer Aided Engineering (CAE), Computer Aided Manufacturing (CAM) b) Virtual manufacturing (VM) c) Enterprise Resource Planning (ERP) d) Manufacturing Execution System (MES) e) Software Integration of quality results with planning and control software (SI) f) Manufacturing Resource Planning (MRP II) g) Inter-company networks including Extranet and electro data interchange (EDI)

h) Wireless communications for production (WCP) i) Sensor network and integration (WSN) j) Computer integrated manufacturing (CIM) k) Automated systems for inspection (ASI; e.g., vision-based, laser-based, X-ray, high definition (HD) camera or sensor-based) l) Unmanned aerial system (UAS; e.g., drone)
Processing and fabrication (PF)
a) Flexible Manufacturing Cells (FMC) or Flexible Manufacturing Systems (FMS) b) Lasers (LSR) used in materials processing (including surface modification) c) Robot(s) with sensing or vision systems (ROBS) d) Robot(s) without sensing or vision systems (ROB) e) 4-9 axis computer numerically controlled (CNC) machinery f) Additive manufacturing including rapid prototyping for plastics and 3D printing for plastics (3DP) g) Additive manufacturing including rapid prototyping for metals and 3D printing for metals (3DM) h) Additive manufacturing including rapid prototyping for materials other than plastics or metals and 3D printing other than plastics or metals (3DO) i) Automated machinery for sorting, transporting or assembling parts (AMST) j) Plasma sputtering (PS) k) Micro-manufacturing (MM; e.g., micro-machining or micro-moulding) l) Microelectromechanical Systems (MEMS)

The following sections review each technology and its history to facilitate interpretation of the results. The functionality of each technology is explained so it is easier to understand the complementarities between each one of them. This section will be very useful to help understand what patterns of technologies can be expected to be found once the results of the analysis are later explored in this dissertation. Figure 3.1 shows a brief diagram of how these technologies are connected. The goal of this section is to understand which technologies have complementarities. This will help in predicting patterns or bundles of technologies that are adopted together. As it will be discussed in Chapter 4, there are two different methodologies to explain bundles of technologies. It is possible to either analyze which technologies have been adopted today regardless of their time of adoption or in which order these technologies have been adopted.

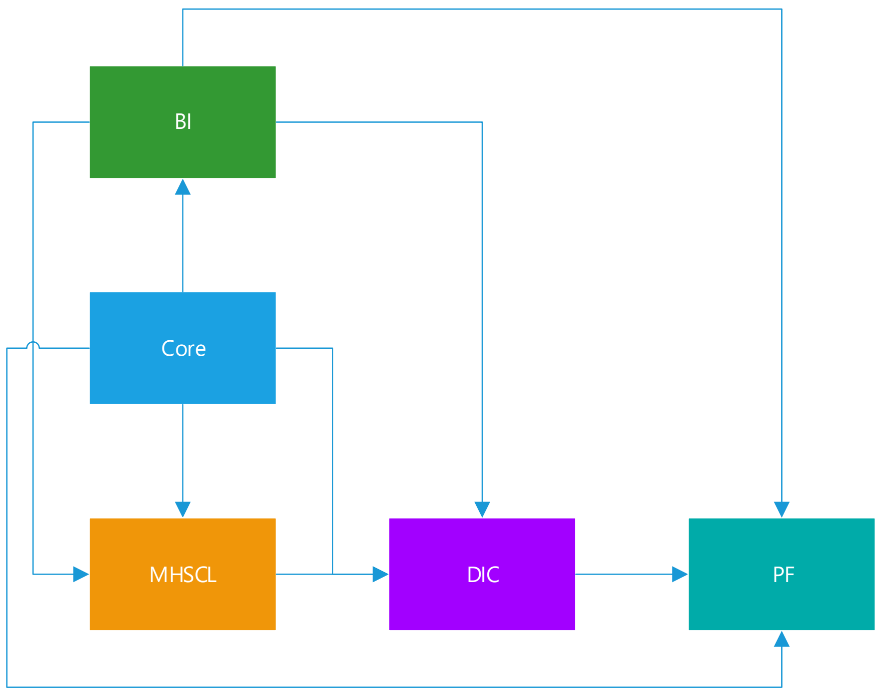


Figure 3.1: Relationships between the 4 main families of technologies in SAT 2014

Based on its core activities or its industry, a firm can choose to adopt one or more of the families of technologies shown in Figure 3.1. The arrows in this figure are intended as a proposed flow for the order in which a firm might adopt these families of technologies. Firms might need some kind of BI tool even if it’s just a spreadsheet. However, there is nothing preventing a company from only adopting the DIC or PF technology directly. This is the case because most of the software today (unless it’s purely intended for manufacturing) have analytical capabilities. Although a firm may be specialized in one type of technology (e.g. BI or PF), it will often require other types of technologies to run its business. For example, if a firm is specialized in advanced manufacturing (PF), it will often require some technologies from all other categories. In fact, to do advanced manufacturing, material handling equipment might be required (e.g. MHSCL). Furthermore, to produce a product, it needs to be designed with DIC technologies. Finally, it would be logical to think that these firms might also require BI tools to analyze their customers, their production process, or other aspects of the business.

It is worth noting that BI technologies are expected to be the only family that will have complementarities with all the others. In fact, BI represents anything related to analytics and any kind of firm will need to collect data whether it is from its tools, machines, robots, etc. The other technologies are more industry-specific. Retail companies for example will mostly adopt MHSCL technologies, while purely manufacturing firms will most likely tend to buy DIC technologies. DIC technologies will be closely related to PF technologies as was previously mentioned. The PF family is largely reserved to firms that have adopted advanced manufacturing techniques and it is expected to see a lower adoption rate. The next few sections will describe the details of each technology for the four main categories to allow better understanding of how each technology is linked with each other and how firms can plan to use them in their core activities.

3.1 Material Handling, supply chain and logistics

Material handling supply chain and logistics technologies consist of many tools that help improve daily operations as well as reduce costs. A number of the technologies covered in this section may appear as stand-alone tools. However, most of them can be integrated with an Enterprise Resource Planning system (ERP), which belongs to the Design and Information Control category that will be presented later. ERP represents an integrated suite of tools that gathers data from many business activities that can include data on customers, employees, production capacity, etc. Some of these technologies are directly integrated into an ERP, the history of which will be presented in section 3.3. Furthermore, several of these technologies were available as a cloud solution, thus rendering them affordable to smaller companies that do not have enough capital to invest in these expensive tools. ERP is frequently cited in the literature as being an essential SCT technology (Hendricks et al., 2007; Mishra et al., 2013). Section 3.2 will discuss the role of cloud computing in business intelligence and the benefits it brings when combined with other technologies.

Before presenting each technology, the logistics chain (Figure 3.2) needs to be addressed to understand where these technologies fit in. Figure 3.2 provides a mapping of each step of the process flow within such chains. Its six constituents have very clear roles as explained by:

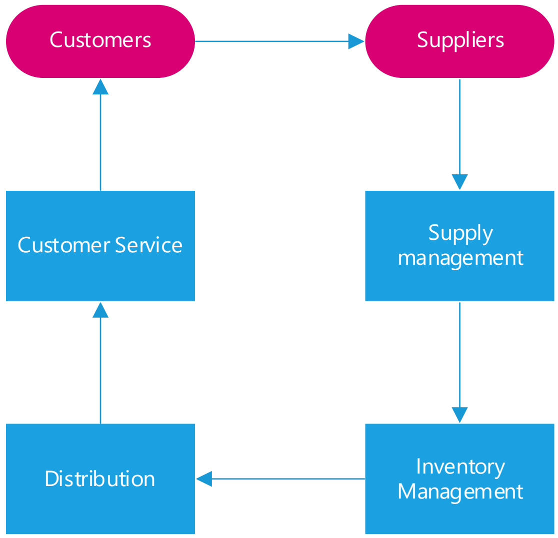


Figure 3.2: Chain of logistics - Process Flow

1. **Suppliers:** The suppliers are usually the first link to the chain of logistics. This is where a company must look to get finished products or raw materials. Suppliers can produce raw materials or a manufacturing firm that produces finished products.
2. **Supply management:** In this step, there will be a search for potential suppliers as well as everything related to planning, organizing, ordering and receiving raw materials or products.
3. **Stock management:** Once all raw materials and products are received, they need to be stored in a warehouse or a distribution centre. This step is important because the number of stocks available as well as their location is crucial to allow distribution to customers.
4. **Distribution:** When a customer orders a product, it goes to a warehouse or distribution centre where the order will be processed. Products sold will also be dependent on a mode of transportation. Not only can products move between warehouses, but they must also reach their final destination, which is the customer.

5. **Customer management:** Customer service management includes all processes aiming to analyze and understand the needs of clients.
6. **Customers:** Based on the type of firm, customer can be other businesses, retailers or consumers. For example, a company like Kellogg's might only sell to retailers while a company like Amazon will sell directly to consumers.

The different technologies that can be used to enhance the chain of logistics will be presented in the paragraphs below. Based on these, it will be possible to draw expectations on which technologies will be closely related. This will allow to get a better understanding of how the technologies fit together and what adoption behaviours can be expected to be found in the results.

3.1.1 Customer Relationship Management (CRM)

"CRM is a process companies use to understand their customer groups and respond quickly – and at times, instantly – to shifting customer desires." [1] A CRM tool lets companies collect data about their customers and use it to adopt strategies based on that information. These strategies will result in insights into customers' behaviours which allow a company to have a tailored targeted strategy. Although CRM technologies are a marketing tool first, they can also impact supply chain management as well product development based on customer data. The concept of CRM has been in use since the early 1990s (Buttle & Maklan, 2019). Prior to that, businesses had to rely on spreadsheets and lists to categorize customers. The first CRM product was designed by Tom Siebel (Siebel Systems) in 1993. At that time, there was a growing interest in automating sales processes using call centres and computer applications (Abdullateef & Salleh, 2013). In addition to stand-alone CRM solutions, companies like Oracle and SAP started embedding CRM modules in their established ERP.

[1] https://www.bain.com/insights/management-tools-customer-relationship-management (Page viewed on Apr 1, 2020)

In 2004, CRM solutions started migrating to the cloud, hence opening their usage to small firms, which could then start using them because it involved a cheaper option. One of the first open-source CRM was developed around that time as well. Because there were so many different CRM solutions, prices started to decrease which made CRM even more accessible[2]. In 2009, social CRM started trending and becoming more popular as companies used social media networks like Facebook and Instagram to buy products. Around 2014, most CRM solutions were linked to Business Intelligence systems (BI) which greatly improved analytical capabilities of customer data. The year 2014 was also pivotal for BI in general, a concept which will be discussed in the next section. Different CRM providers include Microsoft, Salesforce and Oracle.

More recently, CRM have evolved into CRM 2.0 or social CRM due to the popularity of social media. Many studies focus on the technological evolution of CRM within the world of social media and their impacts on consumer behaviour (Malthouse, Haenlein, Skiera, Wege, & Zhang, 2013; Sigala, 2011; Trainor, 2012). This new trend of social CRM has led firms to increase their investment in this technology (Kunz et al., 2017). However, very few firms have a strategy to implement social CRM. According to Dickie (2013), only 11% firms had a formal CRM strategy. There is an uncertainty amongst organizations as to whether they are making full use of social CRM (Debnath, Datta, & Mukhopadhyay, 2016). It is expected that firms will make more use of this technology in the future because it allows them to personalize customer experiences and interactions (Acker, Gröne, Akkad, Pötscher, & Yazbek, 2011; Faase, Helms, & Spruit, 2011; Trainor, 2012).

3.1.2 Software for demand forecasting or demand planning

Demand forecasting (DF) use data and predictive analytics to plan what is going to happen in the future. For example, if a company sold 10 items this year, it might sell 10 items next year. In the early days of forecasting, methodologies were reactive to historical data. In other words, whatever happened in the past would happen in the future. Once statistics were introduced to DF, firms could

[2] http://comparecamp.com/introduction-history-crm-software/, page viewed on April 8, 2020

get a better forecasting accuracy by adding different parameters that would account for seasonality and trends.

Forecasting then evolved into demand planning which allowed to incorporate casual effects into the forecast. This allowed models to be accurate when looking at aggregate data. Casual effects such as new product launches or pricing discounts could be added by the users into a demand planning software. This software would ensure an accurate forecast for the whole firm and predict future demand. However, once that forecast was broken down into location or markets, there was more noise as volumes were smaller, which in return resulted in more volatility and less accuracy.

Today forecasting has evolved into much more accurate models that use machine learning to predict the future. Similar to CRM tools, demand forecasting or demand planning software has also become incorporated with business intelligence tools for better prediction capacity.

Finally, there are a lot of different aspects to look at when selecting the best software to use such as its scalability potential as well as the post-implementation support. However, one of the most important one is its compatibility with an ERP system. As previously mentioned, CRM tools are being integrated into an ERP and it is the same for DF software because it needs to be able to easily read customer or revenue data from an integrated suite of applications.

3.1.3 Transportation Management System (TMS)

TMS is a platform or a tool that helps businesses with the physical movement of goods. TMS is often part of the supply chain visibility and collaboration system (see subsection 3.1.5) and its goal is to plan and optimize the transportation of goods. Transportation can be by air, sea or land and have different regulations and documentation associated with each mode of transportation. A TMS also considers scheduling information in order to optimize all transport operations.

In today’s world, TMS is also available in a cloud-based solution which make it more affordable for smaller firms to adopt this technology. In fact, before cloud computing became available, smaller firms had to rely on Excel spreadsheets to manage their transportation of goods.

With more firms starting to adopt Industry 4.0 technologies, the future of TMS is rapidly evolving by embracing innovations that can allow for same-day delivery as well as real-time tracking of a delivery. These technologies include Internet of things (IoT) which allow devices and sensors to monitor goods in real-time. Nowadays, machine learning and block chain also have a role to play in modernizing TMS. Because of its close ties to data collection, this technology is expected to be combined with business intelligence technologies to further enhance its benefits.

3.1.4 Warehouse Management System (WMS)

As an extension to a TMS, firms will have warehouses to manage all the products they sell. Instead of using spreadsheets, they can adopt a WMS to support and optimize their distribution centre and warehouse. While a TMS is used to support the transport of goods from a warehouse to a customer or business, a WMS supports the planning and organization of resources into, within and out of a warehouse. This software is most often used in complementarity with a TMS if a firm sells a lot of goods. Like all other operational software, a WMS can be stand-alone or integrated as part of an ERP. The cloud version also exists. In fact, cloud will eliminate the need to install hardware or hire IT consultants to maintain a WMS, which makes it less expensive and more accessible to smaller firms. In addition to being integrated to an ERP, WMS will also connect to barcode technology to track materials and goods. This can allow the software to find stocks within a warehouse, as well as suggest transfers between warehouses to balance quantities.

Because it is often part of an integrated suite, it can be expected to find this technology with other operational software such as a CRM and a TMS. Barcode technology will be further discussed in subsection 3.1.7 but it is considered complementary and even essential to take full advantage of WMS technology. Understanding the functionalities of these technologies is useful for formulating propositions on the patterns of technologies that firms are adopting. For instance, while WMS, CRM and TMS can be part of an integrated suite, their goal is similar. They are a form of database that stores information on specific business activities such as the warehouse storage, customers and the transport operations respectively.

3.1.5 Supply chain collaboration and visibility systems (SCCVS)

In 2013, Gartner defined end to end supply chain visibility as “a capability that provides controlled access and transparency to accurate, timely and complete plans, events and data – transactions, content and relevant supply chain information – within and across organizations and services to support effective planning and execution of supply chain operations.” [3] In other words, it is mainly a tool to facilitate collaboration between all actors of a supply chain process, from manufacturers to suppliers. Companies can collaborate with external actors by giving them access to forecasts and inventory information in real-time. The visibility provided by SCVVS enables partners to stay connected inventory fluctuations that happen within complex supply chains (Christopher & Lee, 2004). Intelligent dashboards that can grant quick information on issues and allow suppliers to react in a timely manner are also part of this technology. Finally, it enables a better onboarding process allowing greater collaboration on projects affecting the supply chain. According to Barratt and Oke (2007), SCVVS enables information sharing between all supply chain actors, which can result in an enhanced supply chain management (Jonsson & Mattsson, 2013; Lumsden & Mirzabeiki, 2008). However, it should be noted that SCVVS requires the adoption of technologies based on automatic identification (Auto-ID) (Angeles, 2005; H. Lee & Özer, 2007), such as Radio Frequency Identification (RFID) that will be discussed below. As a consequence, it is expected that SCVVS and RFID will be adopted as part of the same bundles of technologies.

3.1.6 Automated Storage (AS) and Retrieval System (RS)

AS/RS are systems used in manufacturing, distribution centres and retail. These systems are guided by a computer in order to track and retrieve items. In addition to a computer, AS/RS systems require a storage and retrieval machine (SRM) which can move objects horizontally and vertically. There are primarily two types of AS/RS – the traditional one that is crane-based (CBAS/RS) and the more advanced autonomous system that is vehicle-based (AVS/RS). CBAS/RS are very common in warehouses around the world. They consist of an automated crane, conveyors and storage racks

[3] https://blogs.oracle.com/scm/collaboration-and-visibility-in-the-supply-chain, page viewed on April 15, 2020

(Burinskiene, 2015). The automated crane can store and retrieve loads by moving horizontally and vertically in narrow aisles between the storage racks. The second type of AS/RS system is the result of advances in Autonomous Vehicle (AV) hardware technologies. AVS/RS is a newer and more technology, which can help improve efficiency by replacing the fixed-crane traditional system. AVS/RS brings many more advantages compared to CBAS/RS. In fact, it grants more flexibility in changing the number of autonomous vehicles and can be adapted to different types of warehouses. AVS/RS can take the form of shuttles that can travel on the floor or even climb vertically to extract a mini-load.

Many benefits come with the adoption of AS/RS technology such as a reduction in labour costs for transporting items as well as a better tracking of the inventory and where items are stored. Automated material handling will also result in an increased storage density. More items can be stored in narrow aisles allowing firms to optimize their distribution centre or warehouse space. These systems also provide gains in ergonomics and safety as repetitive and complicated tasks are done by a crane or a robot. These systems play an important role in increasing space capacity as well as productivity. They are expected to be used in complementarity with a WMS, mainly as such tool is required to manage items stored in a warehouse. Nowadays, AS/RS systems are important because of the important volume of online orders that occur every day.

3.1.7 Automated products and parts identification (e.g., bar or QR coding)

Bar and QR coding are way of identifying and labelling inventory which can include consumer products, equipment or other parts. A barcode is series of bars and white spaces which can translate into numbers and characters. Theses bars can then be read by a scanner. Barcodes have been around since over four decades and are usually one-dimensional (1D). They are mostly used in retail applications since it is scanned when a consumer purchases a product. Barcodes can store a variety of information such as the manufacturer's identification number as well as the item or product number. There are many types of barcodes not just for warehouses and distribution centres but also for libraries. For example, ISBN codes are present on almost all book covers and can help track a book. Barcodes are still widely used nowadays because there are inexpensive and help speed up the supply chain process. Combined with material handling technologies, they can greatly reduce manual labour costs as well as allowing accurate inventory management.

Furthermore, Quick Response (QR) coding is an evolution of barcodes. It is a two-dimensional code (2D) that was first created in 1994 in the Japanese automotive industry. Because they are 2D codes, they can store a lot more information than the traditional barcode. They can store email addresses, names, products details, websites URLs, etc. QR code is a matrix that can store up to 1520 alphanumeric characters. Both types of codes are widely used today but QR coding continues to get more popularity as smartphones are able to scan them very easily without the need to download an app. Most social media apps also have QR codes to quickly add a profile or a connection. Moreover, because of their matrix format, QR codes are easier to scan compared to the traditional bar coding that needed to be scanned in the same direction.

Combined with AS and RS, QR/Bar coding become extremely essential to manufacturers and firms that have large warehouses of distribution centres. The ability to quickly identify parts and materials is crucial especially when there is an ERP to manage the supply chain process as well as other aspects of a company. It would be expected to see this technology adopted in complementarity with AS and RS since retrieval systems require some form of tacking code to be able to quickly identify a product.

3.1.8 Radio frequency identification (RFID)

RFID is more advanced than barcodes or QR because they use an electromagnetic field to identify and track objects. This can be done through a tag consisting of a radio transmitter, attached to an object. It requires an RFID reader nearby to which the tag in the object will transmit digital data containing its identifying number. This number would be stored in a database allowing this technology to improve the inventory of goods. Unlike bar and QR coding, an RFID reader works by being near an object. The object does need to be scanned in a specific angle. Some tags can be scanned at a greater distance because they contain a battery that can amplify the signal emitted.

It is believed that the predecessor of RFID was in fact a radar as listening device. The device was invented for the Soviet Union by Leon Theremin in 1945 and it was activated by waves from an outside source (ISECOM., 2008). Although it functioned similarly to an RFID, the first true predecessor of this technology was a device invented by Mario Cardullo (Cardullo, 2005). His device was patented in 1973. Ten years later, the first RFID patent was granted to Charles Walton in 1983[4].

There are many applications for this technology, especially in manufacturing and retail. It is a good way to track goods and parts without the need to have a barcode being scanned in a specific angle. Since the device sends a signal with an identification information, RFID is also used to track animals, airport luggage, clothes in retail. For example, RFID can help prevent shoplifting by tagging clothes in stores. This tag would have to be removed once the customer has paid for his item. Since most stores will have an RFID detector at the store's entrance, any customer leaving with items that still have a tag would be noticed because an alarm would sound right way, allowing to identify that an item hasn't been paid. The grocery supply chain is another sector where RFID can play an important role. For instance, Martínez-Sala, Egea-López, García-Sánchez, and García-Haro (2009) proposed an idea that consisted in using intelligent returnable packaging in combination with a software to track transport units. Such tags make it possible to gather and share information with supply chain actors (Attaran, 2007; Spekman & Sweeney, 2006).

With Internet of Things (IoT) becoming more and more important nowadays, RFID can play an important role in transportation and logistics. Distribution centres and containers shipments on boats would have RFID tags that allow for tracking and identifying of equipment enabling actor to have an overview of material flows (Holmström, Partanen, Tuomi, & Walter, 2010; McFarlane & Sheffi, 2003). With this technology, it is possible to track exactly where an object is in the supply chain process. It is expected to see such a technology in complementarity with firms using TMS and WMS. Based on the industry and the size of the company, it is possible to see RFID adopted with AS and RS. In fact, RFID will be more expensive than QR/Bar coding which might prevent some companies from adopting it if they don't have enough cash flow.

[4] Charles A. Walton "Portable radio frequency emitting identifier" U.S. Patent 4,384,288 issue date May 17, 1983

3.1.9 Conclusion

To understand how these technologies fit into the supply chain process, the technologies in the logistics chain are included (see Figure 3.3). Although many of these technologies can be used in multiple aspects of a firm's supply chain, they are shown for their main purpose. It also gives an insight into which technologies are complementary. A large firm that has the capacity to buy all these technologies will probably adopt them all. In fact, all these technologies can bring important benefits including increased productivity and reduced labour costs. It is also worth noting that most of these technologies can be purchased as stand-alone applications. They don't need to be part of an ERP. They can also be adopted as a service in the cloud which significantly reduces the costs for firms. Analyzing complementarities, it is expected to see bundles of technologies adopted together in the stock management and distribution phases in Figure 3.3. Some companies may opt to not use an AS/RS for example because it is too expensive, but they will surely have QR/bar coding or RFID. A WMS could be replaced by spreadsheets if the company does not have a large inventory or a lot of customers.

Technologies such as TMS and CRM can also be replaced by spreadsheets. However, if one is adopted, it is expected the other to be adopted as well, especially for logistic firms who manage all of their activities in an integrated software suite. If a company has a lot of customers, it will likely have a lot of transportation to manage as well and it would be more efficient to use an integrated ERP that will combine TMS and CRM. A lot of these technologies' adoptions will potentially be influenced by the size of the firm. The bigger, the more likely it will have goods to be delivered to customers. Finally, there is also the possibility that firms might adopt only a few of these technologies pertaining their core business activities and fill in the gaps with spreadsheets or cheaper tools. While a general bundle of technologies will be presented in Chapter 4, it is possible to group some of these tools into three categories: (1) operational software (CRM, TMS, WMS), (2) collaboration and planning tools (SCVVS, DF/DP), and (3) tracking and retrieval tools (AS/RS, QR, RFID).

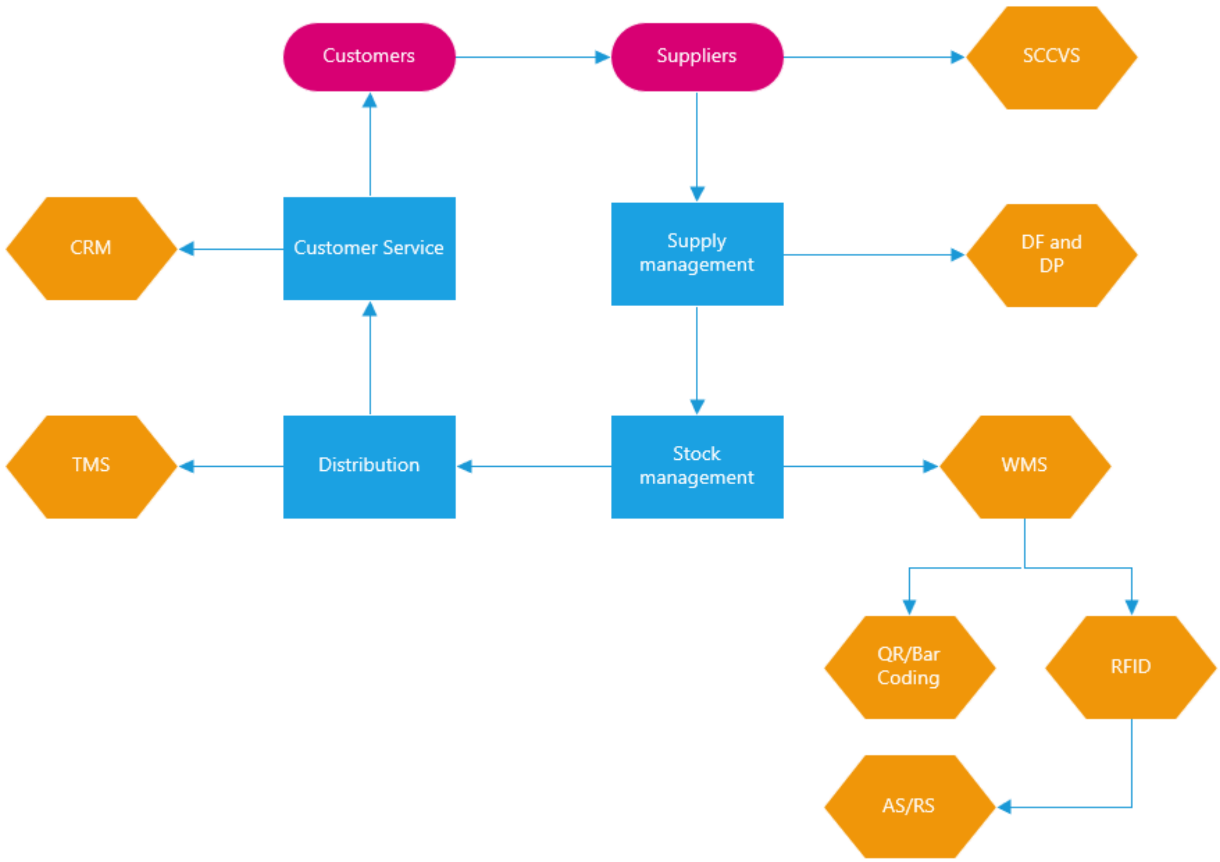


Figure 3.3: Logistic chains including technologies needed

3.2 Business intelligence

To the best of our knowledge, the first use of the term business intelligence originated in Richard Millar Devens' book in 1865:

The name of Sir Henry Furnese figures largely amongst the bygone bankers who gave renown to the financiers of that period. Throughout Holland, Flanders, France, and Germany, he maintained a complete and perfect train of ***business intelligence****. (Devens, 1865, p. 210)*

In this anecdote, Devens describes Sir Henry as a banker that acted before his competitors based on the information he received. This resulted in him gaining more profits than his competitors. In addition to this, there were two other notable mentions of the term BI (Gibson, Arnott, Jagielska, & Melbourne, 2004; Luhn, 1958). According to Luhn (1958), “Business is a collection of activities carried on for whatever purpose, be it science, technology, commerce, industry, law, government, defence, et cetera. The communication facility serving the conduct of a business (in the broad sense) may be referred to as an intelligence system.” He also used the Webster’s Dictionary definition of intelligence as “the ability to apprehend the interrelationships of presented facts in such a way as to guide action towards a desired goal.” In other words, business intelligence can be defined as the analysis of facts to enhance business decision-making. Despite the term being used first in 1865, the wide acceptance of the term has been coined by Howard Dresner from Gartner research in 1989 (Gibson et al., 2004). According to Dresner, business intelligence describes “concepts and methods to improve business decision-making by using fact-based support systems” (Power, 2007). Since then, multiple different definitions of BI emerged, which were reviewed by Chee et al. (2009). They reviewed BI definitions according to three categories: managerial and process, technological and product. The review only focussed on what’s relevant for this research and presented the definitions that explained what a BI technology is. These definitions can be found in Table 3.2.

Table 3.2: Summary of technological BI definitions (Source: Chee et al. (2009))

Source	**BI definition**
Adelman & Moss (2000)	A term encompasses a broad range of analytical software and solutions for gathering, consolidating, analyzing and providing access to information in a way that is supposed to let an enterprise’s users make better business decision.
Moss & Atre (2003)	It is an architecture and a collection of integrated operational as well as decision-support applications and databases that provide the business community easy access to business data.

Table 3.2: Summary of technological BI definitions (Source: Chee et al. (2009) …con'td and end)

Moss & Hoberman (2004)	The processes, technologies, and tools needed to turn data into information, information into knowledge and knowledge into plans that drive profitable business action. BI encompasses data warehousing, business analytics tools and content/knowledge management.
Oracle (2007)	A portfolio of technology and applications that provides an integrated, end-to-end Enterprise Performance Management System, including financial performance management applications, operational BI applications, BI foundation and tools, and data warehousing.
Hostmann (2007)	An umbrella term that includes the analytic applications, the infrastructure and platforms, as well as the best practices.
Turban et al. (2007)	An umbrella term that encompasses tools, architectures, databases, data warehouses, performance management, methodologies, and so forth, all of which are integrated into a unified software suite.

To summarize, BI refers to the applications that integrates structured and unstructured data in order to guide manager make better business decisions. As pointed out by Azevedo and Santos (2009), BI has three different approaches that can be found in Figure 3.4. The first approach is the traditional approach and consists in summarizing the data to provide different ways to view and analyze to data. Tools such as Data Warehouse (DW), Extract, Transform and Load (ETL), Online Analytical Processing (OLAP), Data Mining (DM) are widely used in this approach. These tools are widely used to help create reports and forecasting that can help improve decision-making for managers. For example, a DW is necessary to store the data, while OLAP is an important process to aggregate data and make reporting easier. In fact, this approach is mainly about data aggregation and data visualization (Kudyba & Hoptroff, 2001; Raisinghani, 2003; Turban, Sharda, Aronson, & King, 2008).

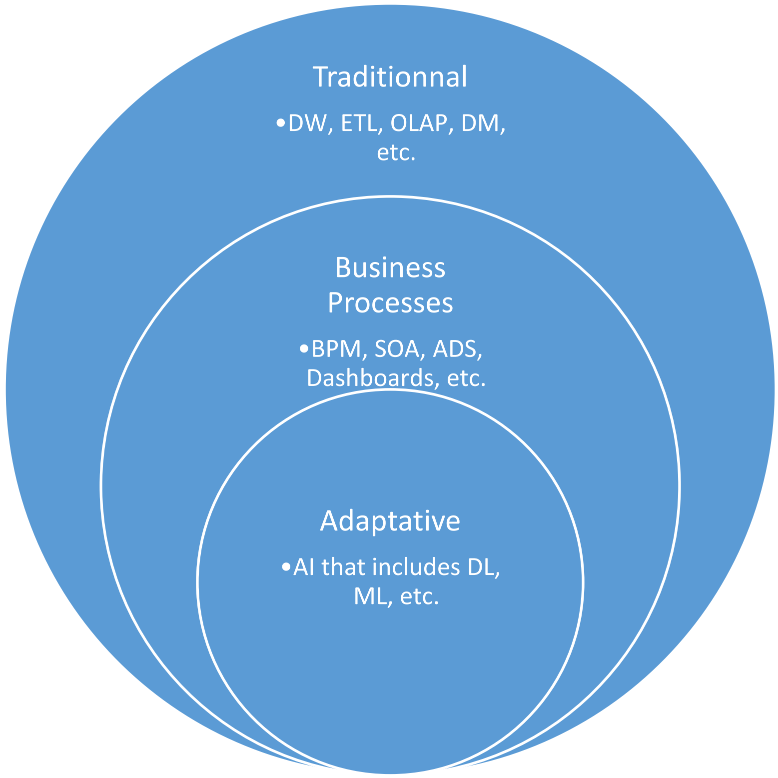


Figure 3.4: The approaches to BI (Adapted from Azevedo and Santos (2009))

The second approach adds a layer to the first approach. According to Zeller, 2008, this layer bridges the gap between business process management and business strategy. The literature studied this approach as an integration of business processes (Eckerson, 2009; Golfarelli, Rizzi, & Cella, 2004; Turban et al., 2008). These tools include Business Performance Management (BPM), Service-Oriented Architecture (SOA) and Automatic Decision Systems (ADS). They also include dashboards which a combination of multiple reports summarized in a matrix or other visualization methods.

Finally, the last, and most important, layer nowadays integrates Artificial Intelligence (AI) with all the previous BI tools and methodologies mentioned. A brief taxonomy of AI is shown in Figure 3.5. Today, one of the most common methodologies to apply AI is to use machine learning (ML), which can self-learn and adapt to changes in the environment. It is easy to see the potential that a self-learning algorithm can have when it is integrated with a dashboard for example. Over the recent years, one of the most common approaches to ML algorithms is to apply deep learning (DL) methodologies (LeCun, Bengio, & Hinton, 2015). In fact, DL algorithms have been able to use a large amount of data to uncover potential predictions (Marcus, 2018). Information systems have benefited a lot from AI that enabled many applications in different industries. For instance, the healthcare sector has seen major advancements in diagnosis and prediction by analyzing images such as breast and lung cancer detection (Katzman et al., 2018; Yu et al., 2016) as well as cardiovascular risk prediction (Ambale-Venkatesh et al., 2017; Poplin et al., 2018). ML and DL also have many applications in smart-manufacturing technologies (J. Wang, Ma, Zhang, Gao, & Wu, 2018), which will be discussed further below in section 3.4.

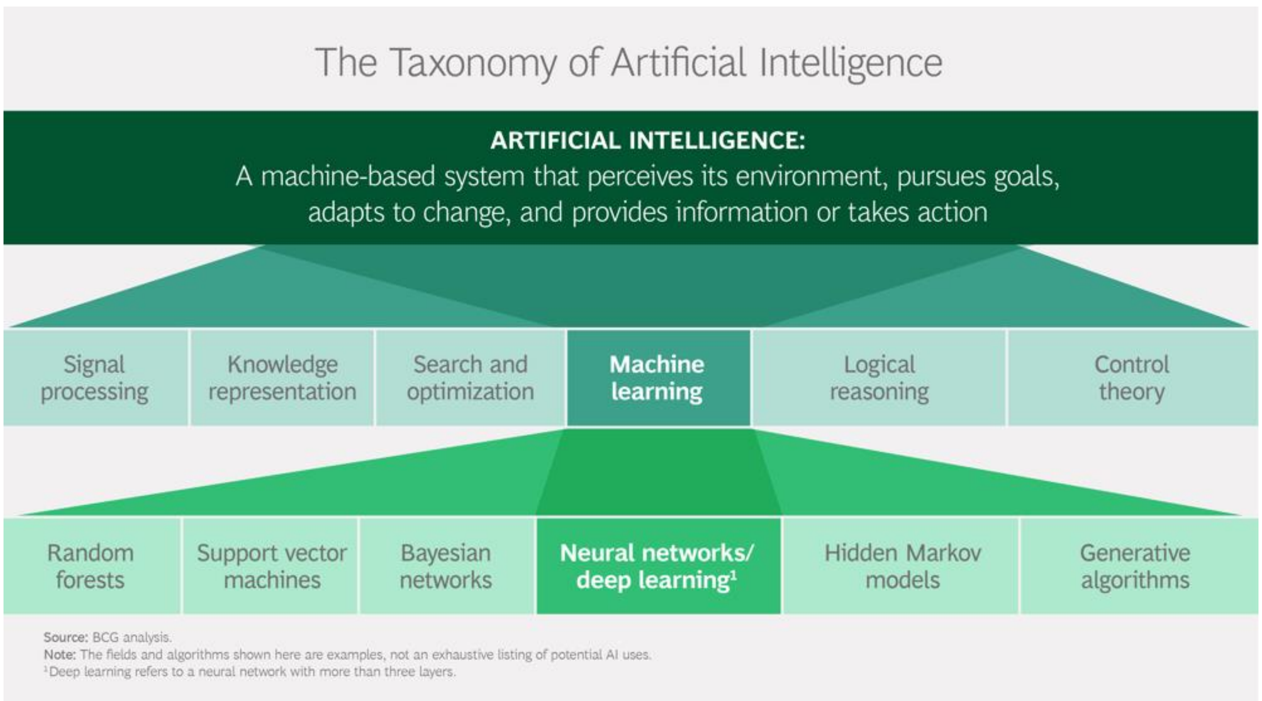


Figure 3.5: Taxonomy of Artificial Intelligence (Source: BCG Analysis)

3.2.1 Executive dashboards for data analytics and decision-making (ED)

Executive Dashboards (ED) allow executives to quickly get insights on critical business decisions that need to be taken. Dashboards are usually a mix of tables and visuals that contain as important key performance indicators (KPI). Data can be normally viewed in real-time, but in most cases, there is a certain lag in which data needs to be collected and shown in a dashboard. For example, for a company wanting to view the efficiency of their technicians, it's not often available in real-time and there is a one-day lag.

ED has many benefits that include improving employee performance and increasing revenues. These can be done by taking key decisions based on data that is displayed. Dashboards are normally web-based and include a cloud version, which means they can be viewed from anywhere in the world. ED often includes collaboration tools as well as mobile access. Executives can most often use filters and drill-down the data to deep dive on other aspects of the business very quickly. They are normally easy to use and can give access to multiple sources of data.

Before ED software came out, dashboards were built in Microsoft Excel. In fact, some can be more sophisticated with macros and be refreshed dynamically while others are more static and need to be updated manually. These dashboards have evolved today into software such as Power BI and Tableau that allow for multiple visualization options that aren't available in a tool such as Excel. Any company with large amount of data coming from multiple sources would have adopted some form of ED today. Tableau was launched in 2012 while Power BI was released in 2015. While the adoption rates of these specific tools are not available, it is known that they're two of the most adopted in the world according to an analysis by Datanyze[5]. One of the most important benefits of these tools is that they enable for multiple users to be in the platform at the same time, which in return can help increase collaboration. It also eases decision-making because more than one executive can look at the same report while changes are being done in real-time.

3.2.2 Software for large-scale data processing (e.g., Hadoop)

Large-scale data processing of "big data" is a field that consists about finding ways to treat large data sets that cannot be stored or analyzed in traditional tools. For example, as of the latest version, Microsoft Excel cannot exceed 1,048,576 rows in a sheet. Even if it does not reach that maximum

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[5] https://www.datanyze.com/market-share/business-intelligence--243, page viewed on April 17.

number, the performance of Excel will be affected if dealing with large amount of data. Big data can be defined as large data sets that cannot be handled with traditional software tools used to capture and process it within a reasonable time (Snijders, Matzat, & Reips, 2012). A more recent definition indicates that big data requires parallel software and servers running to handle the data (Fox, 2018). Therefore, to deal with large amount of data in a tolerable time, big data software (BDS) was born. Although the most important characteristic of big data was its volume, it's no longer true today. There are other important aspects to examine including the variety, the velocity and the veracity and quality of the data. The variety means that data can come from different sources but also in different formats. Based on the operational system from which the data is collected, the format can typically be texts, numbers, images, etc. Velocity represents the speed at which data is collected. As was briefly covered in supply chain technologies, RFID enables IoT and can allow data collection from thousands of objects in real time, but the right framework and software need to be used so that this collected data can be used instantly. Data is often generated in a continuous stream and it becomes important to know when to collect it and how often to publish it. Because data is generated and stored without any manipulations, its quality might be impacted because it is only assessed when analysts start to analyze it.

Firms committing to structuring their data by implementing a BDS are seeking modern techniques to analyze this data by using machine learning and natural language processing, for example. The infrastructure, as seen in Figure 3.4, is the core to implementing a BDS. Although it is possible to use the more traditional approach (e.g. a data warehouse), using a BDS requires a Data Lake (DL). One of the most used frameworks for processing large-scale data is Hadoop. It is open-source, which greatly lower the costs of adoption. It has not yet completely replaced the traditional approaches. Moreover, Hadoop is difficult to use. In fact, firms require very specific skill sets to implement and maintain Hadoop. According to a survey by CrowdFlower in 2016, 83% of respondents said there was a shortage of data scientists, up from 79% in 2015[6]. This number is likely to continue to grow. Therefore, data warehouses (DW) remain a necessity to work with

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[6] Source: https://www.bcg.com/publications/2016/big-data-advanced-analytics-technology-digital-look-before-you-leap-into-data-lake, page viewed on Sept 18, 2020

structured data in a relational database. Although Hadoop was first released in 2006, it is not anticipated to have a high adoption rate of Hadoop or a similar BDS around 2015 because of its complexity. Another challenge that is faced with this technology is that it does not yet have the same standards of security as traditional DW.

3.2.3 Live-stream processing technology or real-time monitoring (RTM)

The goal of live-stream processing is to allow an analysis and decision-making process in real-time. This is done through the use of continuous queries on a database. Before defining the concept of live-stream processing, it is important to define event processing, which is a tracking method that analyzes data about events that are occurring (Luckham, 2011). From event processing, Complex Event Processing (CEP) can be derived, which is the ancestor of live-steam processing. In fact, CEP was developed in the early 1990s to identify opportunities (or threats) in real-time and act quickly upon them. CEP represents the methods used to track, process and extract real-time information. CEP has been widely used by companies in the financial industry to create algorithms to improve stock trading returns. Other industries such as airlines or telecommunications firms have been using this concept to monitor their assets and take instant decision as data is being processed. The concept of live-stream processing takes CEP one step further because it allows for massive volumes of data to be processed in real-time. With today's IoT adoption rates expected to climb drastically, RTM becomes more and more important because of the size of data that needs to be quickly processed to allow instant decision-making.

Assuming that firms are using RTM technologies, it is impossible to know if they are using software that's based on CEP or live-steam analytics. It is logical to believe that some firms would have been using CEP with fewer data while others would have important amounts of data requiring live-stream analytics. Since both technologies are basically doing the same function, they can be considered as the same, with the only different that one is a more advanced version of the other. Furthermore, it is highly likely that RTM will be based on a BDS that can quickly collect and store the data to allow live-stream processing. Traditional approaches to collecting data that involved a DW required the data to be updated periodically (e.g. hourly, daily or weekly), which would add a delay to view it and take decisions upon it. As a consequence, it can be assumed that companies that have adopted an RTM have likely adopted some kind of BDS to process the large volume of data generated. It is anticipated to find RTM and BDS adopted as part of the same bundles of technologies.

3.2.4 Software as a service (SaaS) and cloud computing software

SaaS represents one of three types of cloud-computing together with infrastructure as a service (IaaS) and platform as a service (PaaS). SaaS is another word for using a third-party application on the Internet. One of the most widely known examples is Microsoft Office 365 or Google Docs. Traditionally, Microsoft Office applications needed to be installed on a desktop and it was only possible to use them on the computer on which they were installed. With the SaaS era, it is possible to log in on the Internet and access an application from any computer and from anywhere in the world. This is possible because such applications are provided by third-party companies on their servers. As was seen with supply chain and logistics technologies in section 3.1, there is almost no limits to which technologies can be used as a SaaS.

The idea of having more than one person connecting simultaneously to the same computer was born in 1963 with Project MAC. Project MAC was founded in 1963 at the Massachusetts Institute of Technology (MIT) and its main goal was to have multiple people access the same computer from multiple locations in the world. The word virtualization was used to describe the concept but its definition started to shift in the early 1970s. In 1969, ARPANET, the ancestor of the Internet, was developed to allow everyone to be interconnected wherever they might be in the world. By that time, the new meaning of the word virtualization described the creation of a virtual computer that operated exactly like a normal computer. This virtual machine needed the Internet to be accessed, which then led to the modern definition of cloud computing in the 1990s. In 1999, Salesforce a company that produces a very popular CRM tool became an example of using cloud computing. The tool could be purchased without leaving the office. In 2006, Amazon launched their cloud computing service, Amazon Web Services (AWS) while Google followed in the same year with Google Docs. A year later, Netflix launched its service using cloud computing. Many other companies followed and by 2014, SaaS was becoming so popular that security became the primary focus of many firms. Today, SaaS is considering very secure for customers and as many other benefits for companies.

Although some companies prefer to keep their software and data stored in their data centres, there are many benefits to adopting SaaS technologies. First, it is less expensive because the hardware infrastructure is not necessary anymore. In addition to that, these tools are charged as monthly payments and can be cancelled at any time allowing firms to try different software to find the best one that would suit their needs. If they need to change a software at a later date, there is no opportunity cost as everything is provided by a third-party firm. SaaS also comes with frequent and automatic updates to include the latest development in a software. There is no need to buy a new version and many functionalities get added on a regular basis based on customers' feedback. Furthermore, it's accessible from anywhere in the world as long as there is Internet enabled on the device, which makes the use of SaaS very flexible. Finally, data from these tools can be stored in the cloud (managed by the provider) or locally. Using application programming interfaces (API), firms can integrate SaaS with other software that were developed in-house. SaaS is expected to have high adoption rates amongst firms, especially the smaller ones, because the costs are not so important using the "pay-as-you-go" model. It is also worth noting that because all other technologies in the BI family can be used as SaaS, it is expected to see different bundles including SaaS.

3.2.5 Infrastructure as a service (IaaS) and cloud computing hardware

If SaaS refers to software that can be used anywhere, IaaS refers to hardware or infrastructure that can be used anywhere. In fact, IaaS provide firms with a server and storage in the cloud. One of the most popular examples is Dropbox where you can store terabytes of files and access them from anywhere and on any computer in the world. Companies who would have adopted SaaS would be expected to adopt IaaS at the same time. In fact, both aspects can become expensive and overwhelming to deal with for firms that don't have the IT expertise. Mostly, tech companies would be a key customer for companies offering SaaS and IaaS. For example, Google not only offer SaaS with Google Docs and Gmail, but it also offers additional storage in the form of IaaS. Today, many companies like Microsoft and Google also offer you to have access to computer power for machine learning projects that requires a lot of memory and computer power to run. In this case, instead of IaaS, it is referred to as PaaS. These environments are equipped with software development technologies such as Python and Java. In return, the finished code can be shared with other users through the platform. PaaS has currently the lowest market share compared to SaaS and IaaS because it is more recent. Although it was not very popular in 2014, it is starting to get more popularity today with the developments in machine learning and artificial intelligence. For example, Microsoft Azure is an example of PaaS that offers the capacity to its users to develop software in the cloud.

3.2.6 Conclusion

These technologies are highly complementary, but they do not need to be adopted all at once. In fact, when adopting SaaS, there is a high chance that IaaS is adopted as well because of the complementarity that has been mentioned previously. Figure 3.6 shows how these technologies can be connected. ED and RTM will most certainly be fed data by a BDS. If companies have not adopted a BDS like Hadoop because of its complexity, they could still have adopted ED and RTM only. In that case, data will be fed through a DW. Although this option is not available in the survey, it can be assumed that most firms will have their data stored in some form of relational database. However, BI only accounted for five technologies and it is difficult to divide them into subgroups like it was done for MHSCL. Furthermore, SaaS and IaaS are considered to be medium of technologies. In particular, SaaS could have been used for all software, including CRM, TMS and WMS. The survey does not provide information on whether a software was used in the cloud or as a desktop application. With the exception of SaaS and IaaS, the other three technologies enable firms with data analysis tools. The literature in Chapter 2 demonstrated that BI increased connectivity and play a key role in productivity improvement (Bantau & Rayburn, 2016; Breur, 2015). Therefore, these technologies could be playing a role in facilitating collaboration and enabling a higher propensity to innovate.

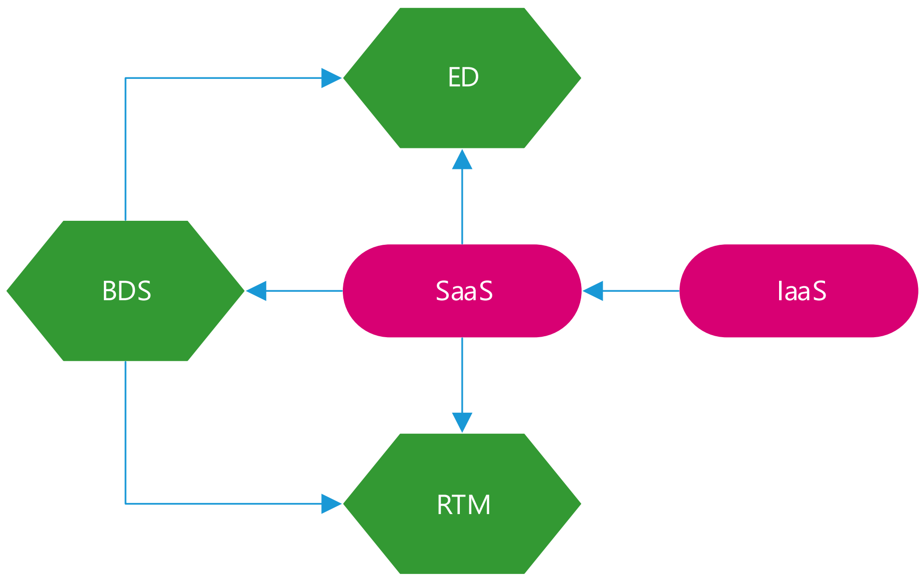

Figure 3.6: Diagram of BI technologies

Furthermore, most of the supply chain and logistics tools would be running on a database. For example, if a firm has adopted CRM, it could have adopted ED as well without the need of a BDS. It is also expected to see a lot of firms having adopted SaaS and IaaS without anything else. In 2014, it was still early to do machine learning and the need for BDS was starting to ramp up. BI tools are essential to improve business processes but are not essential to execute the core activities of companies. For example, it is expected for firms to adopt CRM and TMS or other tools specific to their core business before adopting BI technologies. Since most of these core tools will need SaaS to function, SaaS and IaaS should be part of a very popular bundle, especially for firms who want to save costs and start implementing important technologies rapidly without taking care of the IT process.

3.3 Design and information control

The manufacturing industry has been led by three industrial revolutions so far: the first involves mechanical production, the second focussed on mass production, and the third phase consisted in the introduction of digital manufacturing. The first industrial revolution made mechanical production possible with the discovery of steam conversion into mechanical work. Around 1760, heated power produces steam that was powering anything from the textile industry to train and railroads. The second industrial revolution started with a number of key inventions such as aircraft and chemical fertilizer. In fact, these discoveries helped the world produce more and faster. It is at the same time that Ford's Model T was built on an assembly line in factories. Finally, the third industrial revolution introduced Information Technology (IT) in factories. Around the 1950s, many new technologies were brought to life such as semiconductors, computers as well as the Internet. This era of digitalization allowed the start of automated production in supply chains.

IT in manufacturing has been a consequence of the growing demand in product customizations. The revolution in manufacturing is based on the digital factory concept, which states that simulation and production data management systems should be jointly used before starting the production process (Westkämper, 2007). The IT integration of design and simulation tools have many benefits including the following: (1) decrease in development cost and time; (2) collaboration with other companies or suppliers; (3) decentralization of manufacturing processes; (4) integration of data and knowledge coming from different departments. Many technologies have contributed to the digitalization of manufacturing. For example, material planning tools were introduced in the 1970s. Computer-aided design (CAD) also played an important role in increasing productivity by reducing the time required to develop a product. Similarly, computer-integrated manufacturing (CIM) was introduced in the late 1980s provided many benefits in product quality and time to market. Figure 3.7 shows an illustration of the manufacturing process flow, from the initial concept to the final assembly. This section reviews the technologies involved in the design and information control phases of the manufacturing process.

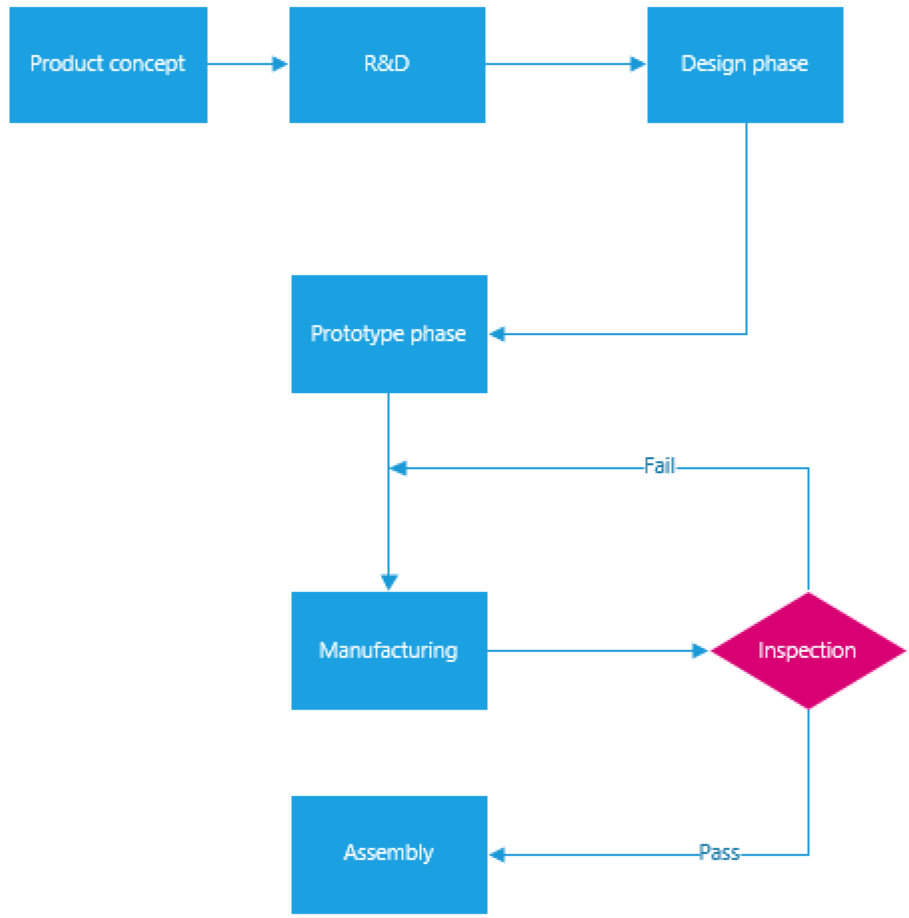

Figure 3.7: Design and manufacturing process

3.3.1 Virtual Product Development or modelling software

Virtual product development (VPD) is the process of developing products with the help of a virtual machine (e.g. a computer) in a 2D/3D environment. There are three main ways to develop a product virtually:

1. Computer Aided Design (CAD)
2. Computer Aided Manufacturing (CAM)
3. Computer Aided Engineering (CAE)

These different technologies allow for product design, simulation, staging and manufacturing and it's all done through a computer. It is common to find tools that can take care of all three types of VPD combined. However, CAD is mostly intertwined with CAM and most software companies offer both types into one integrated suite. The following paragraphs will present a brief history of CAD, CAM and CAE as well as their purpose.

CAD is mostly used to design and create 2D/3D illustrations and models. One obvious example of CAD utilization would be a plan representing a building construction project that gives details on the foundations, the electrical wiring, the mechanical components, etc. The first ancestor of CAD was called PRONTO (Program for Numerical Tooling Operations) and was developed in 1957 by Patrick J. Hanratty. His version of PRONTO is believed to be the building blocks to everything that is known as CAD or CAM today. He then developed DAC (Design Automated by Computer) four years later, which was one of the first graphical CAD systems. This technology continued to evolve over time to add computer vision capabilities in 1975 and many geometric modelling features in 1981. One year later, AutoCAD was born and became the first CAD software made for PCs. 3D functionalities were added in 1994. In the late 1990s, other companies followed by introducing additional tools for 3D design (e.g., SolidWorks, Solid Edge, CATIA). Although CATIA was the first tool to be available online, it wasn't until 2012 when Autodesk 360 made the move to the cloud that other companies followed. As was mentioned in previous sections, the main benefits of using a software in the cloud and adopting SaaS is the cost of implementation that is greatly decreased.

Unlike CAD, CAM is not for designing. It is intended as a tool to automate manufacturing processes. Because CAD is so intertwined with CAM, the latter can read designs from the former which in return increases the accuracy and efficiency of the manufacturing process by adding automation. The early days of CAM started around 1950 with the development of Numerical Control (NC). NC or computer numerical control (CNC) is a virtual manufacturing manual that contains instructions and specifications to be executed automatically by a computer. For example, a CAM can control the path for the cutter of a CNC or the trajectory of robots. As the use of CNC became more popular, the MIT worked to develop a universal programming language, which is the G-Code as it is known it today. The G-code contains a series of instructions to speed up the manufacturing process. These instructions can be either programmed or transferred directly from a CAD. The evolution of CAM is not so different from CAD as features were added gradually and more complex and advanced manufacturing technologies were developed. These technologies will be the main focus of section 3.4, but it should be noted that CAM plays an important role ensuring these advanced manufacturing techniques are executed properly.

Before a designed product is sent to manufacturing through a CAM, some simulations might need to be run in order to ensure that the product will work as intended. This is where a CAE tool can be very useful because it allows to simulate the impact that different effects and conditions can have on the end product. Having the ability to test before the product is even created increases costs saving and the quality of the final design. For example, if calculations need to be carried out before sending a design to manufacturing, a CAE may be used to do specific simulations. It is difficult to pinpoint an exact date on when CAE was first used as it involved many fields and methods such as computational fluid dynamics (CFD) and finite element method (FEM). Both these methods started around the early 1940s. The main evolution is that CAE became more integrated with CAD to allow simulations based on the design. Many different tools exist such as Matlab and Abaqus. The former first got released in 1984 and has over 3 million active users today while the latter is specifically designed for FEM was first released in 1978. Many of these tools are developed by the same providers of CAD and CAM which makes the integration between the three types easier.

3.3.2 Virtual manufacturing (VM)

Like VPD, virtual manufacturing (VM) uses computers to model and optimize production in a factory plant. VM uses virtual reality (VR) technologies to achieve its goals by providing a simulation environment that reproduces manufacturing systems. According to a PwC survey, the most common application of using VR technologies is to do product design and development (38% of respondents)[7]. VM is in fact very tied to VPM because they use similar tools in order to simulate a product before sending it to an assembly line. Because of that, it could be expected to see VM

[7] https://www.pwc.com/us/en/industries/industrial-products/library/augmented-virtual-reality-manufacturing.html, page viewed on June 22, 2020

and VPD adopted together quite frequently. However, both technologies can also be seen as a substitute to the other. One of the most common uses of the VR is through an interface that allows a user to interact with a simulation. The benefits allow a full inspection of a product without incurring any costs of production. This is a powerful tool that can contribute to reducing production costs while also increasing product quality. VR can provide environment in which engineers can interact with an object in 3D to improve decision-making. Benefits of the adoption of VM (using VR technologies) can be achieved in the different steps of the manufacturing process such as in planning, simulation and even in assembly and inspection. For example, VM is useful to achieve design credibility during a simulation (Rohrer, 2000) and can also provide more understanding during interdisciplinary discussion about a product design. Furthermore, it can help reduce design cycle time (Jayaram, Connacher, & Lyons, 1997) and provide an environment for reviewing inspect methods (e.g. collision detection, inspection plan) (W. Lee, Cheung, & Li, 2001).

Finally, in addition to simulation and manufacturing purposes, VM can be very useful in developing training for employees because it grants them the possibility to view the entire factory in a virtual environment. Users are then empowered with the ability to explore the outcomes of their decisions while being in a safe environment. As was previously mentioned, VM can be complementary to VPD because it adds a view not only in the design phase but also in the subsequent phases of manufacturing and inspection.

3.3.3 Enterprise Resource Planning (ERP)

As briefly highlighted above, the concept of Enterprise Resource planning refers to the management of main business processes which include supply chain management, customer relationships, accounting, human resources, amongst many others. This process is often managed by a software that contains integrated applications that can collect and store data from the different business units. From the technologies that were already covered in this research, ERP can normally integrate CRM, WMS, TMS and most of the other supply chain and logistics technologies in section 3.1. The following paragraph will explain all the different aspects of business that could be integrated into an ERP software. This task will clarify how all the technologies are connected, not only for this section but for the other families of technologies as well. The main modules of an ERP software are shown in Figure 3.8.

Figure 3.8: The main modules of an ERP software

There are many more modules, but those highlighted in orange consist of the technologies used in this research. Most of these modules can be stand-alone software or fully integrated into an ERP suite. The customers, sales and procurement modules mostly relate to CRM but will also have BI tools that will be able to forecast the demand (DP and DF). Distribution and supply chain management are more related to material handling technologies such as AS/AR, QR/Bar coding and WMS, as well as TMS. These technologies consist of organizing and optimizing distribution centres, retrieving products and material needed and arranging transportation once they need to be shipped. Finally, the product development module focusses on manufacturing mostly known as MRP II (Manufacturing Resource Planning), which will be explained below.

The ERP acronym was used in the early 1990s by Gartner to address all activities related to manufacturing. However, ERP modules regarding all business activities started to be integrated around the mid-1990s. By 2000, ERP was starting to become widely popular amongst different industries. This rapid growth was led by the “millennium bug” which made it impossible for old systems to distinguish between the years 1900 and 2000 because most systems used only 2-digits to represent the year in their calendar dates. This led many firms to upgrade previous systems with ERP software based on their core business activities.

3.3.4 Manufacturing Execution System (MES)

MES is a tool that ensures that the process of manufacturing goods is executed efficiently. The system controls everything happening on the shop floor by monitoring and tracking in real-time the manufacturing process. MES started in the 1970s where software applications were used to automate the production process. Although automation was part of manufacturing back then, the term MES wasn’t coined until 1992 by AMR Research (now part of Gartner). In the early 1980s applications capable of planning and controlling the materials used for productions came to life. These applications were known as Manufacturing Resource Planning (MRP and MRP II). MRP and MRP II are an integration of ERP systems. Although they are very good at planning and scheduling, their main downside was that they didn’t collect and report data fast enough. In fact, most MRPs were doing so daily while production on the shop floor requires instant data collection.

In the early 1990s, MRP basic functions of collecting data and scheduling were transformed into what is known today as a MES software. MES evolved over the years to improve data collection and acquisition, scheduling, and performance analysis. These tools also offer document and process management features which reduce paperwork between shifts and improve overall product quality. Nowadays, MES is, of course, integrated with ERP. While ERP have the data on how many customers ordered a product, MES knows exactly how to execute an order that ensures the customers get what they wanted. There are more very useful core functions that make MES an essential technology to adopt. These can include product traceability, product data management as well as supply chain management.

To summarize, MES grants the possibility for decision makers to control inputs, personnel and machines in real-time with the goal of optimizing the current conditions, which will result in an increased production output. Because of its strong ties with ERP and MRP, it is expected to be adopted in combination with either of these tools, if not both. Furthermore, because some firms might adopt stand-alone software to complement a MES tool (for example a CRM), it's possible to find complementarities with other families of technologies.

3.3.5 Software Integration of quality results with planning and control software

Quality assurance is the aspect of reviewing all manufacturing activities to ensure that certain quality standards are maintained during production. The quality control is not only made on the final product but include inventory inspections, supplier performance review, document linking and tracking, and many more functions. Because they are many aspects to check, firms often prefer to adopt a quality assurance suite that will track and monitor the business operations to ensure a final product meets the customer's quality standards. Many quality control activities are usually done by advanced manufacturing tools such as robots, which will be discussed in section 3.4.

Although quality results can normally be tracked independently, it is very common to adopt a software integration of quality results with an ERP. As was previously mentioned, this information system tool has the capacity to integrate many business practices such as manufacturing, logistics, inventory, invoicing, accounting, etc. For an example, a defective piece can be quickly tracked to understand which supplier made it and which product it may have been used.

3.3.6 Manufacturing Resource Planning (MRP II)

Manufacturing Resource Planning (MRP II) is not so different from an ERP in the sense that it is a modular software. It’s a system that contains multiple modules aimed at enhancing the manufacturing process of a firm. In other words, it represents an ERP for the manufacturing sector. It ranges from operational planning of materials to complex simulation and what-if scenarios. MRP II can be divided into multiple modules that are integrated into a larger ERP suite of applications. Figure 3.9 shows the basic modules of this information system. However, it is important to note that there are many other systems that play a role in MRP II. As was previously mentioned, CAE, CAM and CAD are crucial parts to designing, simulating and executing the manufacturing process. Other related systems include accounting management, project management and distribution resource planning. Because of

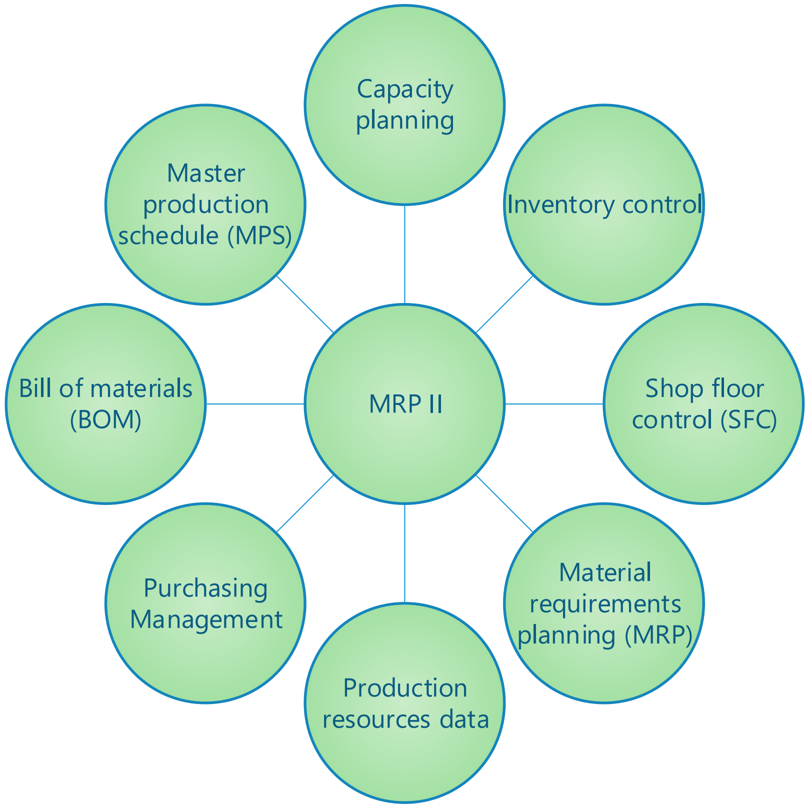

Figure 3.9: The main modules of MRP/MRP II

MRP II can be seen as the predecessor of ERP, because it works with modules but are only specific to manufacturing. However, MRP II is still widely adopted today, either as a stand-alone system or integrated with an ERP. In the 1960s, Gene Thomas developed a database management package aimed at storing the bill of material processor (BOM). BOM consisted in a list of materials, components and other parts including the quantities required to manufacture the final product. In other words, it acted as an instruction manual to increase the efficiency of the production line. Following BOM, MRP was born as a system that could integrate how many raw materials and when they should be purchased. Following this, MRP became a module of larger suite of applications called MRP that not only looked at materials management, but the whole manufacturing process. Since this iteration was in the 1980s, the centralized database storing all the information from an MRP II system was not advanced as today. Therefore, the information was not updated in real-time. Despite some great benefits, many businesses could not afford to implement MRP II because of its high cost. Although MRP II is still used today, it evolved in ERP that has modules not only for manufacturing, but for all other core activities of a business. Finally, it is worth noting this tool tend to be replaced by an MES that can track information in real-time in a much more accurate tool to improve overall product quality. It would be expected to see firms adopting MES as part of an ERP or MRP II tool, which will allow a firm to better control its manufacturing activities.

3.3.7 Inter-company networks including Extranet and electronic data interchange (EDI)

Electronic data interchange (EDI) is the process through which firms can exchange and transmit their data with their partners, suppliers, customers, etc. The origin of EDI goes back to 1965 when the Holland-American steamship line used this technology to exchange information about manifests. The information was then converted in a way it could be uploaded into a computer, making it the first message to be transmitted between two computers. Almost a decade later, the File Transfer Protocol (FTP) was created, allowing to transfer files between Internet sites. Over the years, EDI has evolved to become faster and more secure through encrypted transmission of data. Today, EDI is adopted by most businesses and constitutes an important technology to minimize paper documents. It is also crucial because it eases communications internally but also with other external parties and partners. An intranet is a network that is used to grant access to sensitive information such as customer data, financial data and shipment information. An extranet is an external access to the intranet which can be done through the Internet or a Virtual Private Network (VPN). For instance, this can give suppliers or external partners the permissions to access information on shipment or payments. However, EDI is not specific to any industry and it would be surprising to find specific complementarities with other bundles. To use a simple example, EDI is the main technology behind email, which makes it easier to communicate and share documents. Most companies, if not all, will use this technology regardless of their core business activities. Another common use of EDI consists of having cloud storage that can be shared with employees and with partners that need to have access to specific information. The cloud storage in a similar way as Dropbox or Google Drive would, but with security layers specific to the firm and its partners.

While EDI should be widely adopted by firms, it is expected to have specific complementarities with other tools. As design files from VPD tools may be large and need to be shared with other departments or external partners, EDI technology can become mandatory. On the other hand, because it is expected to be widely adopted, it might not show in any bundles of technologies.

3.3.8 Wireless communications for production (WCP)

Wireless communications for production (WCP) technology enables machines to transmit data to each other and to other people in a manufacturing facility. In a world where IoT becomes even more important, WCP is an essential technology to allow communication between different machines but also between people working on the floor. There are three types of communications in a factory plant: human-to-human (H2H), machine-to-human (M2H) and machine-to-machine (M2M). H2H communication is rather easy to achieve by simply using a two-way radio, which is a wireless device that allows two people to communicate with each other inside a factory. In fact, due to many different machines operating, interference might be problematic, hence the use of two-way radio that is more efficient in small distance communications. M2H communications are a way to improve productive through increasing human safety. Many different products including smart sensors are being implemented nowadays (see section on sensor networks and integration). Smart sensors allow plant managers to track when a worker is exposed to dangerous conditions such as toxic gas or low oxygen levels. These parameters are tracked in real-time which allows managers to take instant actions. These sensors communicate with managers through WCP to ensure workers' safety which leads in return to an increased productivity. M2M communications allow to monitor every stage of the manufacturing process from production to delivery. With WCP, it is now possible to control heavy machinery or robots from a computer with minimal human intervention. There are multiple machines that contribute to automating the manufacturing process with minimal error. These will be explained in section 3.4 on processing and fabrication technologies.

Finally, because WCP is intertwined with a lot of processing and fabrication technologies, it should a complement to robots with or without sensing and vision systems. WCP should also be adopted with sensor networks and computer integrated manufacturing (CIM), two technologies that will be explained in the next paragraph. However, WCP may not have a high adoption rate because it faces some obstacles. One of the most cited ones is the wireless performance that may be perceived to be poor (Vilajosana et al., 2018). Wireless is perceived as a non-reliable technology because the latency that it can achieve is quite high compared to what is normally required (Schindler, Watteyne, Vilajosana, & Pister, 2017). Despite not being the preferred choice, some factories dimensions can make it difficult to use fibre-optic cables, which makes wireless the only possible solution.

3.3.9 Sensor network and integration (WSN)

As was previously mentioned, sensor networks require wireless devices which properly link this technology with WCP. These sensors are distributed in the environment to monitor its conditions that can range from temperature, sound and pressure to heartbeat and oxygen levels. All the data collected through sensors is transmitted through wireless technology allowing machines or people to take guided and proactive decisions. Although there are already more than 100 million sensors deployed in the world today, the technology isn't new. For example, acoustic sensors were used during the cold war to detect submarines. Today, the National Oceanographic and Atmospheric Administration (NOAA) uses similar sensors to detect any events in the oceans. Another important factor in the evolution of this technology is the development ARPANET in 1969. As was previously mentioned when discussing SaaS technology, the predecessor of the Internet was used to connect computers between universities. This led to the development of Wireless Sensor Network (WSN) in 1980 where it was possible to produce tiny nodes that could house multiple sensors. Advances in security and stability have led to WSN being widely deployed in the world. Their usage is constantly increasing nowadays due to their scalability, mobility and low cost. The evolution of processing and fabrication techniques also contributed to making these sensors more advanced than ever. For example, using Micro Electromechanical System (MEMS) has led to a new generation of WSN that is making the IoT a reality. In fact, it is a matter of time before we start seeing WSN to better monitor our roads, manufacturing plants, healthcare, etc. The processing and fabrication techniques including MEMS will be discussed in section 3.4.

There are an infinite number of possible applications. It's not uncommon to see sensors monitoring air pollution, detecting forest fires or monitoring water quality. In the wake of 2020 COVID-19 pandemic, it's not impossible to think that sensors could play a role in preventing or minimizing the effects of a pandemic in the future. Due to its importance, a complementary adoption between WSN and WCP is expected, as both technologies are necessary to each other. However, for WSN to function properly, it needs machines, robots or other kinds of devices from which it can read data. In other words, there could be an added value to have these communication tools with some of the processing and fabrication technologies that will be presented in section 3.4.

3.3.10 Computer integrated manufacturing (CIM)

The concept of Computer Integrated Manufacturing (CIM) relies entirely on the computer to track and optimize the production process. It originated in a book by Joseph Harrington titled *Computer Integrated Manufacturing* (Harrington, 1979). Because everything is controlled by a computer, other related technologies play an important role. Figure 3.10 shows the related technologies that can make CIM function properly. The system considers the design and engineering phases from other tools such as CAE and CAD. There are also material handling technologies that enter the mix. CIM is not useful unless the technologies in Figure 3.10 are adopted as well. Because CIM relies on data and high-quality design, its related technologies are a must (e.g. sensors, MES). Companies who adopted CIM are expected to have also adopted sensors and MES. According to Porter 2017[8], a CIM is a system based on software that integrates assignments and reports from various parts of the factory floor operations through sensors from material handling equipment, ERP modules, MRP modules, design tools (e.g. CAD). Because of all the integrations, it is even possible to use machine learning on the data that can be collected from the factory floor. For instance, a CIM would control the design and simulation that are produced with VPM and send them to the MES, which will then execute the manufacturing process. Through the use of sensors and WCP, data can be communicated back and forth to take proactive decisions and optimize the

[8] https://www.nukon.com/blog/5-key-benefits-of-computer-integrated-manufacturing, page viewed on Sept 9 2020

production process. Finally, material handling equipment can be used to store the finished product or to move it for the inspection and quality tests. These steps can also be controlled by a CIM. Although these technologies might be all adopted at the same time, a CIM is an integration tool that requires other tools to function properly. It should be found in bundles with the related technologies shown in Figure 3.10.

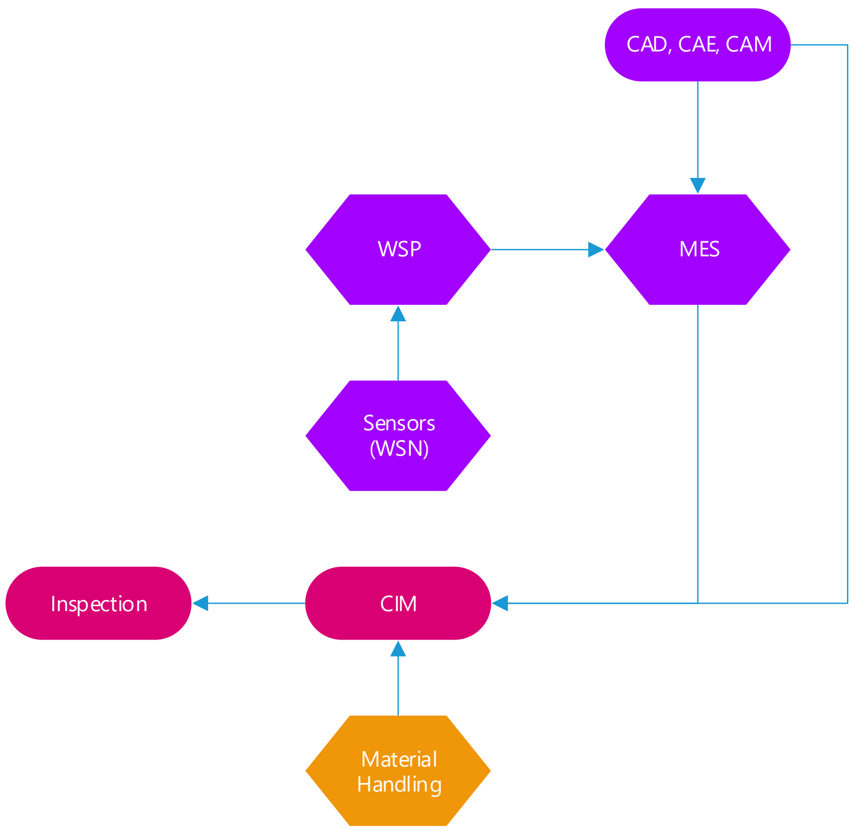

Figure 3.10: CIM and its related technologies

3.3.11 Automated systems for inspection (e.g., vision-based, laser-based, X-ray, high definition (HD) camera or sensor-based)

There are multiple tests that are possible to do after the manufacturing process is complete. Some tests also examine the product after specific steps in the production line. These tests have the main purpose of examining the product to find anomalies, quality defects or missing components. In most cases, Automated Systems for Inspection (ASI) consist of a visual inspection with methods such as automated optical inspection (AOI) and automated X-ray inspection (AXI). The former use optimal vision to inspect visible parts of the product through a HD camera while the later uses X-ray to transmit greyscale images of what's inside the final object. For these tools to work, they use sophisticated computer vision software that allows for pattern recognition and image processing. With today's advancement in machine learning and image processing, these tools have a growing number of applications. For example, automated systems for inspection are widely used in electronics manufacturing, particularly in the semiconductor sector where packaging control quality is crucial (Mustafa, Suhling, & Lall, 2016; Tu & Tian, 2013). Detecting a missing piece or other defects early will reduce the overall cost because it prevents these pieces from being used in subsequent steps. It's much easier to detect a defect early than at the later stages when a product is finished. AXI is very useful in detecting defects, specifically in the semiconductor industry (Holler et al., 2017). In addition to reducing the overall costs, it also provides feedback to managers if something is wrong in the process and needs to be fixed, whether it is defective materials or a wrong design. Firms will seek to adopt such software and tools to increase overall product quality. However, until recently visual inspection still required human expertise to yield accurate results (Sharp, Ak, & Hedberg Jr, 2018), which could mean that ASI are not widely spread yet.

3.3.12 Unmanned aerial system (e.g., drone)

An unmanned aerial system (UAS) is an aircraft that can be controlled remotely on the ground or onboard computer without a pilot on board. Typically, these UAS are referred to as drones. They originated in the military sector and their main purpose was to conduct missions that were too dangerous for humans. The first known use of UAS goes back to 1849 when Austrian forces launched incendiary balloons over Venice. The unmanned balloons were launched from a balloon carrier, also known as the ancestor of an aircraft carrier. During World War I, another type of UAS came to light with the invention of aerial torpedoes that exploded after a certain time had elapsed. The technology kept evolving after World War I and but remained for military applications only. In 1935, the first remotely UAS was developed by Reginald Denny. Over the years, UAS were used for many purposes other than just a weapon. For example, some UAS were used as a decoy in the 1982 Lebanon war to neutralize air defences. In addition to being used a decoy, technology allowed these aerial systems to also have cameras installed allowing countries to conduct surveillance and reconnaissance missions. While circuits were being miniaturized, it opened the door the cheaper and better drones in the 1990s, many of them were used in the Gulf War.

Despite obvious software and telecommunications elements, drones need sensors to function, like the ones that were previously mentioned when discussing WSN. Therefore, there could be many uses in manufacturing and other industries besides the military. With costs falling, drones are becoming more popular and possible commercial applications are emerging. For example, Amazon was looking to adopt them massively to deliver orders that will be dropped with a parachute. To that extent, Jeff Bezos, the CEO of Amazon, revealed in 2013 his plans to launch Amazon Prime Air, a service that could deliver orders in 30 minutes or less with the use of a drone. However, as of April 2020, the service was not launched yet despite being expected to start operating in a few select cities. In other words, although many civilian drones are used today for photography and panoramic video, it takes time to adopt them massively like Amazon is trying to do. They are not expected to be adopted in other industries as well. It is worth noting, however, that drones can play an important role in smart factories and manufacturing. As was previously mentioned with WSN and automated inspection systems, IoT is contributing to increase product quality and reduce costs. Drones can do the same as there can be part of a larger WSN. Drones can find materials, transport them, monitor products defects as well as machine failures. Because of the important role they can play in cargo transport, it would be a possibility to see them integrated with TMS or WMS technology as was discussed in section 3.1.

3.3.13 Conclusion

Most of the technologies that were reviewed are strictly used in manufacturing. They were mapped to illustrate their complementarities. At the time of the data collection in the year 2015, some technologies were already more mature than others, while some were expensive and only used by early adopters. Figure 3.11 shows what is believed to be a map of DIC technologies and where they can be useful in the manufacturing process flow. The three main VPD technologies are displayed on the figure to show how they are connected. It should be noted what while these technologies are believed to be mainly for manufacturing purposes, it is also possible to use a CAD tool to design plans for a construction project. Therefore, CAD and CAE could be expected to be adopted in a smaller bundle without the more advanced technologies that are more specific to large-scale manufacturing.

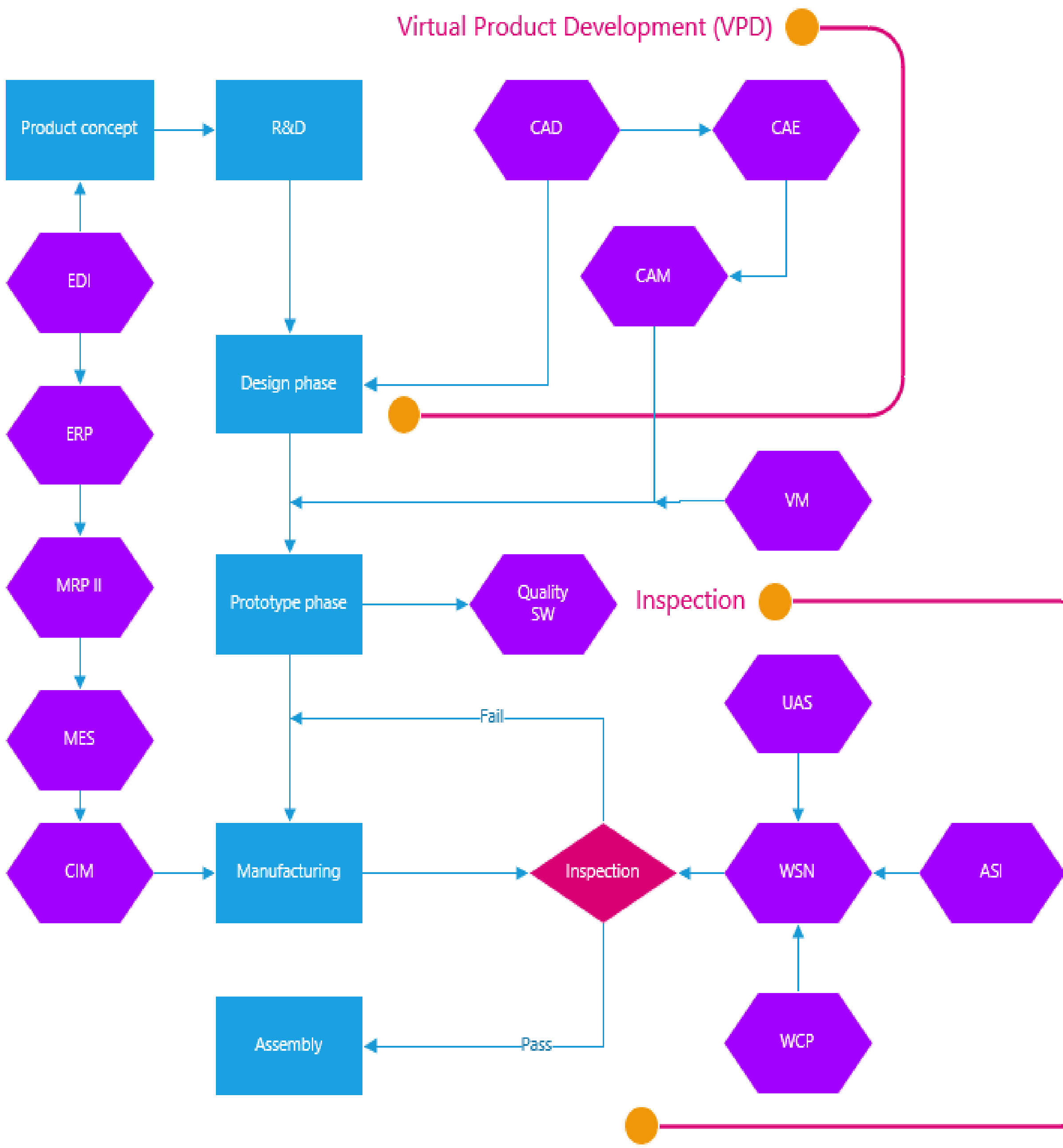

Figure 3.11: The design and manufacturing process and their related DIC technologies

Furthermore, technologies such as EDI or ERP should be implemented for most firms. If ERP is not implemented, MRP II should be adopted to at least assist companies with planning their raw materials needed and manufacturing schedules. Because of the complexity of the technology involved, some bundles might include MES and CIM depending on how much capital a firm is willing to spend. When MES or CIM are adopted, it means a firm has enough capital to integrate its process with computers. Furthermore, the full design process should be done by a bundle of CAx software whether it's for designing, engineering or manufacturing. Finally, the aspect of quality check, inspection and monitoring the environment is done via sensors. WSN should be a central technology adopted for most firms combined with wireless communications (WCP) that allow the sensors to communicate with each other. The adoption rate of drones is expected to be fairly low and because of that, very few bundles will include this technology. However, because of their use of sensors and cameras, ASI should be popular with WSN and WCP. In sum, these technologies could potentially be divided into smaller groups: (1) design software (VPD, VPM), (2) operational software (ERP, MRPII, MES, CIM, SI), (3) communications and information sharing (WSN, WCP, EDI), and (4) quality assurance software (UAS, ASI). It would be expected to find many different groups of technologies in the same bundle based on a firm's industry and core activities. These bundles should also have complementarities with the processing and fabrication technologies that will be discussed next.

3.4 Processing and fabrication (PF)

Processing and fabrication (PF) are the process in which raw materials are transformed into a product that can be sold to customers. Before the industrial revolutions powered by steam, heavy machinery and automation, manufacturing required skilled workers that could perform tasks by hand. There were no computers and advanced software to handle each step of the design and manufacturing process. While most workers were in rural areas, customer demand was difficult to be met as there was only a limited number of skilled people to do the job. There many different additions that made manufacturing more efficient, such as digitalization (see section 3.3) and automation through the introduction of robots. While these technologies have resulted in cost reduction and increased quality products, it is the fourth Industrial Revolution that truly enabled the next age of manufacturing. Many of the technologies that will be presented in this section make what is referred to nowadays as "Industry 4.0". They are transforming industrial production in a way that is completely flexible. The strength of these technologies is in their complementarity. In fact, Industry 4.0 happens because many technologies are used together, namely big data and analytics, autonomous robots, additive manufacturing, augmented reality and many more.

Technologies in advanced manufacturing will not replace humans. Despite many autonomous robots being introduced alongside IoT, the future of work will be to optimize the interactions between humans and machines. This section will review some of the advanced manufacturing technologies that currently shape Industry 4.0. It is worth noting that these PF technologies cannot work on their own as they must get their input from DIC technologies that we previously discussed. It will not be uncommon to find many complementarities between PF and DIC technologies.

3.4.1 Flexible Manufacturing Cells (FMC) or Flexible Manufacturing Systems (FMS)

Flexible manufacturing is the process of being able to adapt the type and quantity being manufactured. Its main purpose is to improve efficiency when there is a need to customize products. This increase in flexibility and efficiency leads to lower costs overall. However, implementing flexible manufacturing systems (FMS) requires important investments, which doesn't make it accessible to everyone. The concept of FMS is composed of multiple cells (FMC) that are comprised of similar machines to produce a specific part from the final product. Each cell is able to produce a certain amount of design attributes which makes it easier to customize multiple combinations based on a customer's needs. In other words, FMC or FMS is a manufacturing system that consists of grouped NC or CNC which we briefly discussed in the previous section (see section 3.3.1 about VPD). FMS started to become available in the manufacturing industry in the late 1960s in the United States and in Europe. The concept was based on the work of Jerome H. Lemelson who developed a robot that could perform multiple tasks on manufactured goods such as riveting, conveying and inspecting the goods. He filled many patents in the 1950s that led to the proliferation of FMS 20 years later.

One of the main advantages of FMS is reduced labour costs. The system is fully automated by computers and has a high level of customization possible, which reduces downtime. In fact, the production line does not have to shut down to produce a different product. However, to reach flexibility requires a lot of upfront costs, which is due to the fact that FMS or FMC must be designed in advance to encompass a large variety of products customizations. This can make this technology more accessible to larger firms that may have a high number of varieties in products, hence requiring more flexibility.

3.4.2 Lasers used in materials processing (including surface modification)

The foundations of laser (LSR) technology lie in the work conducted by Albert Einstein in 1917 by predicting the phenomenon of "stimulated emission". In 1950, physics Nobel prize winners, Charles Townes, Alexander Prokhorov and Nikolay Basov developed the quantum theory of stimulated emissions. Their work demonstrated the stimulated emission of microwaves. Building on that theory, Gordon Gould suggests that stimulated light can play a role in amplifying light. Almost a decade after the quantum theory, he proposes an optical resonator that is capable of creating a very narrow beam of light. His theory is known as Light Amplification by Stimulated Emission Radiation (LASER) which sets the foundation for the first prototype of a laser generated by a synthetic ruby in 1960. In 1963, AT&T Labs developed a new method of laser generation that is less costly and has a higher efficiency, using CO_2. In 1967, Peter Houldcroft used a CO_2 laser to cut through a sheet of steel that had 1 mm of thickness. Metal cutting and welding continued to profit for the evolution of lasers. In 1975, the development of the first 2-axis laser system was used in the automobile and aircraft manufacturing industry.

In the 1980s, lasers were able to process plastic and rubber. In fact, laser material processing (LMP) uses lasers to modify the surface of a material, whether it's to cut it or change its properties. Material composition range from metals such as iron, aluminum and stainless steel to plastics and other polymers. LMP technology is used in combination with manufacturing machinery whether a firm is using a single machine of FMC. It must be viewed as a component of a larger machine. In fact, lasers can be used to mark, cut, weld, scribe or alter the properties of a material. Furthermore, material alteration is also known as surface modification allowing the deposition or coating of other materials. By definition, LSR technology is part of other technologies such as FMS/FMC or additive manufacturing (AM) where surface modification is very common. Therefore, they are expected to be adopted with many other technologies that will be discussed next.

3.4.3 Robot(s) with sensing or vision systems

Robots are machines that can perform a series of actions automatically based on information gathered from sensors. In manufacturing, robots are designed to perform tasks that are dangerous for human workers. Such tasks include repetitive actions or dangerous work that can lead to injuries. In addition to increased safety, robots can greatly improve quality and production speed. Like other advanced technologies, robots can require a high investment which is what can slow firms down into adopting them. However, their long-term on investment makes sense. There are many types of robots that can be used in a factory, some of which will use sensing or vision systems. The main tasks performed by robots are presented in the following:

1. **Material Handling:** We previously discussed this briefly with the material handling technologies. AS/AR are robots aimed at storing and retrieving items from shelves. Similar robots can also be used feed raw materials to a manufacturing machine.
2. **Welding:** This type of robot is being adopted massively to its cost going down. Its main purpose is to automate the welding process, which avoid repetitive tasks to be done by human workers. Although, vision or sensing systems are not necessary in this case, many of these robots come with such systems in order to ensure the safety of the workers near them on the floor.
3. **Assembling:** These robots are very flexible and can perform multiple tasks from fixing and inserting to press-fitting. With constant innovation being introduced into manufacturing, these robots have evolved with the introduction of force torque and tactile sensors. This technology allows the robots to perform tasks faster and with increased precision compared to humans. Although many of them come with no sensing or vision systems, the introduction of such systems allows the robots to be even more efficient in localizing parts and in how well they fit together during the assembly phase.

4. **Dispensing:** Dispensing robots are different than the rest as they do not manipulate parts. They are used for applying glue or adhesive as well as spraying paint. They offer high precision and speed up the execution of the manufacturing process. This type of robot can include a camera which allows it to adjust the position and orientation of a workpiece allowing multiple customizations in the final product.

The last steps of manufacturing usually include material removal as well as inspection for quality purposes. These robots can cut and polish the final product, so it nears perfection. Once this step is completed, there are other types of automation that can put in place to inspect the goods produced to ensure the highest of quality. Due to the high number of different robots available, it is not expected that firms will be able to adopt all of them, especially the smaller ones. However, some robots are also reprogrammable and can be repurposed to different tasks. Despite high return on investment, most of these robots require high upfront capital. One solution that companies will be inclined to use is to adopt robots without sensing or vision systems, which is discussed next.

3.4.4 Robot(s) without sensing or vision systems

Robots without sensing or vision systems perform the same tasks as the ones discussed in the previous subsection. These tasks are usually simpler as they involved picking up or placing objects. These robots are often used to perform simple but highly repetitive tasks, which helps increase safety of workers on the plant floor. However, cameras or sensing systems add more accuracy and allow more complicated actions to be performed. Because robots without sensing or vision systems can be less expensive, smaller firms might be more inclined to adopt them if they don’t have the upfront capital needed. Regardless of firm size, we expect to see both types of robots adopted (with and without sensing), sometimes together but most importantly with other technologies. In fact, for robots to be part of a manufacturing process implies that there will be other technologies adopted such as FMS/FMC. LSR and CNC that will be discussed next.

3.4.5 4-9 axis computer numerically controlled (CNC) machinery

4-9 axis machinery is based on CNC machinery we discussed before. They can be controlled by a CAM tool through instructions sent by CAD technology. Traditionally, CNC technology uses three axes: from left to right through the X-axis; from front to back through the Y axis; up and down through the Z-axis. These machines needed to be repositioned frequently to be able to cut through complex angles. Multiaxis machinery offers many benefits including reduced human labour, higher quality parts and increased life of the machine due to it being able to achieve optimal angles. This is done through additional axis that can rotate up to 180^{o} around the X, Y, Z axes. More axes provide the opportunity for firms to develop complex 3D objects. The machinery can access the interior of a product in angles that were not possible with three axis technologies. CNC machinery is used to perform tasks requiring a lot of precision, which is controlled by computer to calculate the exact position and trajectory needed to make modification on a material. This technology can be included as part of an FMS/FMC, which is why it can be expected to see both adopted in the same bundle. Due to the precision required by CNC machinery, LSR can also become a component that will be adopted with it. CNC relies on a subtractive process rather than an additive process that consists in producing objects layer-by-layer, which is similar to a two-dimensional printer where a third dimension (z-axis) is added (Reeves, 2009). This technology is discussed next.

3.4.6 Additive manufacturing (AM) including rapid prototyping for plastics and 3D printing for plastics

The concept of additive manufacturing (AM) consists in creating solid 3D objects by using a material (plastic, metal, or others) and combining it with light (usually a laser). The first photopolymer was invented by DuPont in the 1950s. Early attempts and research to create solid objects using light and photopolymers date back to the 1960s. However, Additive Manufacturing (AM) technology surfaced in the late 1980s, but sales only began to increase in the early 1990s (Kruth, Levy, Klocke, & Childs, 2007). The first use of AM goes back to 1987 with the development of stereolithography (SL). SL is a technique that can create three-dimensional objects by solidifying liquid plastic photopolymer using a laser bream. The required structure is built layer by layer. The first machine was called SLA-1 and is the ancestor of the once-popular SLA 250 machine, which got replaced today by the Viper SLA. This technology can produce 3D objects by feeding into the printer a design produced by CAD technology. Many other technologies and processes have been developed over the years and with patent expiration, low-cost 3D printers were starting to get more traction. 3D printing technology is generally used for two purposes: Rapid Prototyping (RP) and Rapid Manufacturing (RM) (Feenstra et al., 2003; Levy, Schindel, & Kruth, 2003; Santos, Shiomi, Osakada, & Laoui, 2006). RP is meant to be used in the product development phase does not offer the same durability and quality of an end product (Feenstra et al., 2003). A prototype is not meant to be equivalent to the final product of parts. With technological advancements, RP has evolved into RM by using layered manufacturing techniques (Rudgley, 2001). In contrast with RP, RM consists in producing functional parts that will be used in the final production process (Regenfuss et al., 2005; Voet, Dehaes, Mingneau, Kruth, & Van Vaerenbergh, 2005). Table 3.3 shows some of the key dates pertaining the evolution of AM technologies.

Table 3.3: Key dates regarding additive manufacturing and 3D printing technologies

Date	**Information**
1987	First commercial use of SLA technology for creating 3D objects Development of Digital Light Processing, a technology used in 3D printing
1991	Commercialization of new AM technologies including fused deposition modelling (FDM), solid ground curing (SGC) and laminated object manufacturing (LOM).
1992	Selective laser sintering (SLS) 3D printing became available
1996-1999	Introduction of low-cost 3D printers for just under 10,000$ at the time using processes similar to FDM and LOM.
2000-2010	First commercially viable SLS printer and gain in popularity in FDM technology.
2013+	Patents expiration on FDM technologies which made them more accessible at a lower cost

Starting in the 2000s, many technologies started to see their patents expire. This opened the door to other companies for developing lower-cost 3D printing machines. However, this technology remains an expensive one despite bringing many benefits and a good return on investment. In addition to cost effectiveness, AM brings a lot of customization potential alongside an unlimited choice of shapes and geometry. It is mostly used to control waste production but to limit the risks of developing a new product. Thanks to the different AM techniques testing a product has never been easier. There is no doubt that this technology will continue to change the industry and is expected to have higher adoption rates and more applications in the coming years. In terms of materials used, most of the 3D printing technologies are made for plastics and metals. Some of them use other materials such as paper or ceramic, for example. Table 3.4 presents a summary of the most important 3D printing technologies on the market today as well as which material they can print. It is not uncommon for a firm to print different materials and it is worth noting that some printers can print both plastics, metals, and even other materials.

Recent research has found many benefits of adopting 3D printing and AM technologies including flexibility and adaptability, design and product customization and reduction of waste (Holmström et al., 2010; Niaki & Nonino, 2017; Weller et al., 2015). One of the main advantages of AM is the fact that flexibility and complexity are easily achieved compared to traditional manufacturing (Weller et al., 2015). The flexibility benefit is especially true for SMEs as this high-level customization can result in operational cost savings (Mellor et al., 2014). Furthermore, due to the reduction in manual labour, some manufacturing activities, that were normally done overseas in lower-wage countries, can be transferred back to high-wage countries (Berman, 2012). This can bring production closer to customers, which can increase service levels for customers ordering customer 3D printed products (Khajavi, Partanen, & Holmström, 2014). The freedom of design that 3D printing and AM enable increases the chances of meeting customer needs (Diegel, Singamneni, Reay, & Withell, 2010) as well as making mass customization of products possible (Niaki & Nonino, 2017). By integrating customers in the value creation process (Oettmeier et al., 2017), AM can provide a competitive advantage due to its flexibility in being able to adapt to varying customer demands (Weller et al., 2015).

The multiple economic benefits provided by AM adoption make it an essential technology for firms nowadays. Due to its important integration with other steps of the manufacturing process, it can also be adopted with other technologies such as VPD. In fact, for AM to work, it needs to have tools that can properly design products to be printed. Furthermore, 3D printers use laser-based technology to be able to modify materials properties, which means we could expect to find LSR in combination with 3D printers. Many of the different 3D-printing technologies can be found in Table 3.4.

Table 3.4: Summary of the main 3D printing technologies

Technology	**Description**	**Material**
Stereolithography (SLA)	Fast prototyping process that led to the first 3D printer in 1987. Plastic is heated with a laser beam to become semi-liquid before turning into a solid state. The printing is done layer by layer.	Plastic
Digital Light Processing (DLP)	Similar to SLA but uses a traditional light process. It is faster and can contribute to reduce costs because of material flexibility.	Plastic
Fused Deposition Modelling (FDM)	The process uses thermal plastic materials to print the objects that are built layer by layer. The end products are very durable but will need hand sanding and finishing once the printing is complete. It is one of the most used technologies due to its lower cost.	Plastic
Selective Laser Sintering (SLS)	Process that uses CO_2 lasers to create bonds between materials. Although its main utilization if for metals other materials are also common such as nylon powder, glass, and ceramics.	Metal, other
Selective Laser Melting (SLM)	The process is similar to SLA in the way that it counts lasers to melt and fuse objects together. The main materials used are powdered metals.	Metal
Electron Beam Melting (EBM)	This technology is very similar to SLM (see above), the only difference being the power source which is an electron beam instead of lasers.	Metal
Laminated Object Manufacturing (LOM)	Rapid prototyping and affordable 3D printer that fuses plastics or paper by applying heat and pressure to the materials. Although it is not the most popular method, it is one of the fastest on the market.	Plastic, other
Binder Jetting (BJ)	It uses a powdered-based material that can be made of plastics, metals, sand or ceramics and a bonding agent.	Plastic, metal, other

3.4.7 Automated machinery for sorting, transporting, or assembling parts

An Automated Machinery for Sorting, Transporting or assembling parts (AMST) is used to assemble and to sort parts. An AMST is normally controlled by a computer and is fully integrated with the product line. The main objective of sorting parts is to detect the ones that are defective before the production process starts. Machines that sort or transport parts are similar to the AS/RS tools we have previously discussed in section 3.1.6. Nowadays AMST are capable of collecting a large number of data that can be used to optimize the machinery. For example, AGV, that were mainly used for transportation purposes, have evolved into robots that use AI algorithms that can transport parts directly to workers or machines. Because AMST can be used with robots and other material handling equipment, we expect to see a complementarity in their adoption. In fact, AMST might be adopted with robots with or without sensing systems. Furthermore, this technology is an important step of the manufacturing process, not only because it can sort part but it can also assemble and transport them. Although it can be totally independent from the product line, it is common to see AMST as a stand-alone machinery. For this reason, we also expect to see it adopted in complementarity with core technologies such as FMS/FMC and possibly AM.

3.4.8 Plasma sputtering (PS)

Sputtering is a physics phenomenon in which it is possible to deposit small particles of material on a substrate that have been ejected from a surface due to fast ionization with plasma or gas. Plasma sputtering commonly uses energy ions of Ar+ (argon). The choice of this rare gas can be explained by two reasons: (1) The mass or argon is ideal for collisional momentum transfer to a wide range of metals contained in the periodic table and (2) argon is considered inexpensive because it’s the third most abundant gas in the Earth’s atmosphere (about 1% of the atmosphere). The concept of sputtering isn’t new and can be traced back to the mid-1800s with two experiments: (1) the work of Michael Faraday on vacuum-arc-deposited thin metal films (Faraday, 1838) and (2) the development of Geissler tube that allowed to study optical and electrical properties of glow discharge is rare gases (Cleveland, 2008). Although sputtering was used to study solid-state physics when it was first discovered, today it is known as an advanced manufacturing technology that can mass-produce thin-film products. Its growing popularity is due to 3 main advantages as described by Greene (2017): (1) sputtering is not sensitive to temperature, which means that the technique can be applied to thermally sensitive substrates, (2) when compared to evaporation, it is quite easy to deposit alloys with PS, and (3) the use of low-energy ion is a flexible approach that allows more surface precision on the materials.

There are many different scientific and commercial applications to plasma sputtering. Perhaps the most widespread use is in the production of a computer's hard disk drive (HDD). It is mostly adopted in the semiconductor industry, where thin-film products must be developed at a very small scale, such as in integrated circuits. Many small electrical components are produced through a sputtering process. The technology is expected to be adopted as part of a fully integrated production line including technologies such as FMS/FMC, LSR and ROB (S). Because PS is rather industry-specific, a low adoption rate is expected. Therefore, this could result for the technology to be absent from popular bundles that will be explored. Nonetheless, it remains a technology used to create small-sized products and can be expected to be adopted with the next two technologies we will discuss, namely micro-manufacturing and microelectromechanical systems.

3.4.9 Micro-manufacturing (e.g., micro-machining or micro-moulding)

Micro-manufacturing (MM) is the process of manufacturing parts at a very small size. MM can be used to create both microelectronics and micromechanical elements. Objects need to be smaller than 10 millimetres in size to be considered a micro-part. To reach the level of micro-part, there are processes that can be used. To name a few, bulk MM and surface MM are two of the most common ones. However, micro-moulding and macro-machining are also used across a wide range of industries. For example, micro-moulding is the process very popular in the electronics industry. It consists of moulding a substrate such as metals or plastics into a base shape. On the other hand, micro-machining is very common across the medical and aerospace industry because it helps achieve complex shapes at the micro scale. The process is similar to the one used with multiaxis CNC machinery we discussed previously.

It is also very common to combine more than one MM process and technologies. Multiple benefits emerge from these applications such as a cost reduction and a lot of flexibility and customization potential. However, the main benefits of these techniques are to allow small manufacturers to compete with bigger ones. MM is an accessible technology that allows many smaller firms to produce small-scale part for the medical and aerospace industry specifically. This technology is expected to grow in popularity as more hybrid processes are made possible and more firms can adopt it.

3.4.10 Microelectromechanical Systems (MEMS)

Microelectromechanical systems are a type of technology that can produce micro-products using different techniques including photolithography, chemical-etching and laser fabrication. MEMS is considered a form of micro-manufacturing that requires some form of MM, specifically micro-machinery. The origin of MEMS dates back to 1959 with the invention of two important semiconductor technologies. The first one was the monolithic integrated circuit (IC); the second one was the metal-oxide-semiconductor (MOS) transistor. This technology is very useful to build sensors due to miniaturization of its elements. The first sensors based on MEMS technology were created in the 1960s. Many other types of sensors were then developed to measures many environmental factors such as physical or chemical.

MEMS has many processes that require complementarities with other technologies mentioned in this section. Amongst these techniques, we can find deposition and etching processes. Within etching processes there are plasma etching and sputtering, which means that MEMS and PS might be adopted together by firms. Furthermore, MEMS require MM technologies like bulk or surface micromachining. These methods were briefly explained in the previous subsection and we can expect to see them adopted in bundles with MEMS and PS.

MEMS have multiple applications including sensors, accelerometers (used in many consumer products such as game consoles and cars) and microphones used in mobile phones and portable devices. Perhaps one of the most important applications of MEMS is inkjet printers, which is one of the precursors of 3D printing. In fact, MEMS are component of 3D printers and they can also be printed with AM. It would be logical to see a bundle adoption that includes 3D printing and MEMS.

3.4.11 Conclusion

To conclude this section, advanced manufacturing technologies in the PF family are specific to the types of products that a firm is producing. Some are more specific to the manufacturing industry while others are more common in the medical and the aerospace industry. However, it is possible to find many similarities and dependencies within this family of technologies. For example, the three types of 3D printing, whether used with metals, plastics or other materials have a good chance of being adopted together. Typically, firms use more than one type of material and it is possible to see two or three types of 3D printing adopted in bundles. As was previously mentioned, advanced techniques such as PS, MEMS and MM are also related and could be adopted part of a bundle as well. With 3D printing, they constitute the most advanced manufacturing techniques. These technologies can be used differently based on the industry, but because they are presented in a general way, we expect to see a widespread adoption. Finally, CNC machinery as well as FMC and FMS might be adopted together as they constitute the main method for production. While firms may only adopt one multiaxis CNC machinery, larger firms might have the means to adopt FMC/FMS in complement of CNC machinery.

Figure 3.12 shows the dependencies between these technologies as well as the DIC set of tools that we previously reviewed. It is important to notice that both families (e.g. DIC and PF) are very complementary. In fact, it's not possible to do advanced manufacturing without the tools to design a product. Figure 3.12 shows the possible bundles of technologies looking at both families together. For example, we can expect to see 3D printing and laser technologies (LSR) adopted together with VM and potentially some of the VPD tools. This being said, what a firm chooses to purchase depends on its core activities. Some companies may only provide a 3D printing service while not requiring a fully automated production line. Finally, there are also the support technologies that can be adopted to assist in the factory floor, such as ROB(S) and AMST.

In the next section, the methodology used in this research will be described to understand and validate the complementarities between the different technologies, not just from PF and DIC but from the two other families that were presented as well.

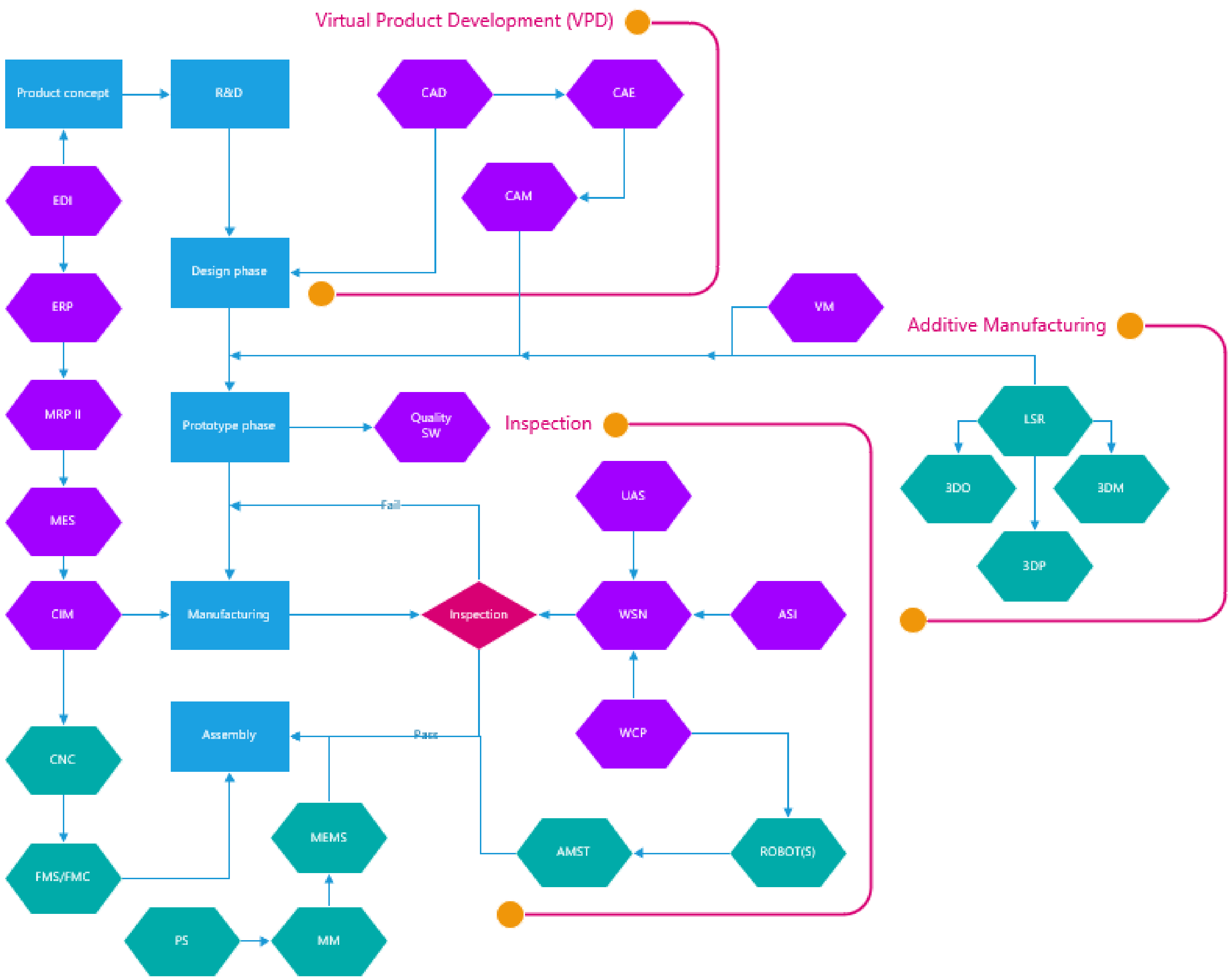

Figure 3.12: Dependencies between PF and DIC technologies

CHAPTER 4 RESEARCH QUESTIONS, OBJECTIVES, AND METHODOLOGY

4.1 Research questions

The focus of this research is on the adoption of advanced technologies as well as open innovation strategies in Canada and its impact on a firm's propensity to innovate. From the review of Chapter 2, it is logical to believe that many firms in Canada have adopted and used advanced technology to increase the propensity to innovate. Furthermore, the survey of the literature presented in the previous chapters highlighted that firms are using OI and collaboration strategies generally tend to increase their performance. This research will also attempt to cover the aspect of public policy and how it can affect technology adoption.

The first set of questions examines the relationship between technology adoption and OI and their joint impact on the propensity to innovate:

1. How does technology adoption and OI strategies influence a firm's propensity to innovate?
2. How do other factors, such as organizational practices, age and size impact a firm's propensity to innovate?
3. What is the impact of obstacles and measures to counter these obstacles on the number of advanced technologies adopted?

The second set of questions that stems from the review of the relevant literature and the exhaustive survey of advanced technologies considers the type of technology adopted by Canadian firms. To explore this, the following questions are of particular interest and will be addressed in this thesis:

4. What are the different technologies adopted by Canadian firms? Are they adopting technologies in bundles and if so, what constitutes these bundles?
5. What are the different characteristics (i.e. size, age, industry, etc.) of the firms that adopt these advanced technologies?

The third and last set of questions focusses on the timing of the adoption of advanced technologies and its impact:

6. Is there a specific order in which these technologies are adopted? How does it change from the bundles explored in questions 3 and 4 above?
7. Do the bundles of adopting technologies change overtime? How will it impact emerging technologies such as IoT and AI in the future?

4.2 Research hypotheses

From the first set of research questions examining the link between technology adoption and open innovation strategies on the propensity to innovate, several hypotheses, based on the literature review, can be formulated. The next section briefly summarizes the relevant literature and proposes the hypotheses to be validated in this thesis.

4.2.1 Collaboration with firms and innovation performance

Firms are required to acquire new knowledge via outside-in activities (Cheng & Huizingh, 2014) because they do not possess all the knowledge needed to innovate (Cassiman & Veugelers, 2006; Chesbrough, 2007; U. Lichtenthaler & Lichtenthaler, 2009). Research has also covered new sources of innovative ideas (Piller & Fredberg, 2009) which reinforces the importance of acquiring outside knowledge. Furthermore, collaboration with external partners, such as other firms or suppliers, proved to have a positive impact on a firm's innovative activities (Dittrich & Duysters, 2007; Enkel, 2010). Moreover, according to W. M. Cohen and Levinthal (1990), internal R&D increases a firm's absorptive capacity and thus its ability to use external knowledge. This ability to access external sources of information have an effect on innovation performance. With better R&D, firms are able to create new knowledge that they can share with external partners (U. Lichtenthaler, 2005) through inside-out activities such as licensing or commercialization. Spinning off a project is another form of inside-out activity since it involves the exploitation of internal knowledge through the creation of a new firm (U. Lichtenthaler & Ernst, 2009a). It can also take the form of contracts, partnerships and alliances according to many studies (U. Lichtenthaler & Frishammar, 2011; Un, Cuervo-Cazurra, & Asakawa, 2010).

Coupled activities is the use of inside-in and inside-out activities. In fact, it refers to the way different players will collaborate in an innovation system (Gassmann & Enkel, 2004). With coupled activities, firms can join forces through a strategic alliance or a joint venture to develop and commercialize new products (Bahadir, Bharadwaj, & Parzen, 2009; Nieto & Santamaría, 2007). West and Gallagher (2006) also studied this concept implying that companies will combine internal and external information to innovate. With coupled activities, firms can build strong ties with innovation networks and partners which will lead to improved innovation performance (Cheng & Huizingh, 2014). As such, firms that participate in collaborative activities with their partners are more prominent to introduce more innovations (Lawson, Krause, & Potter, 2015; Schleimer & Faems, 2016). This conclusion was also observed in supply chain networks where firms that pursue collaboration strategies with other companies see their innovation performance increased (C. Wang & Hu, 2020). The following hypothesis can be derived:

Hypothesis 1: *Collaboration with other firms has a positive effect on a firm's propensity to innovate*

4.2.2 Collaboration with universities and innovation performance

Traditionally, university and industry links were mainly focussed on IP transfers (Perkmann & Walsh, 2007), but these links have been evolving throughout the years to a more multifaceted nature (A. Agrawal, 2001; Bonaccorsi & Piccaluga, 1994; Grossman, Reid, & Morgan, 2001). There are a lot of channels and ways in which firms and universities can collaborate such as: patents, informational information exchange, publications and reports, public meetings and conferences, recently hired graduates, and licenses and temporary personnel exchanges (W. M. Cohen, Nelson, & Walsh, 2002). The relation between industries and organizations becomes an important aspect to main these links (Perkmann & Walsh, 2007; Schartinger, Rammer, Fischer, & Fröhlich, 2002). Jordan and O'Leary (2007) found the interaction between high-tech firms and higher education institutions did not result in more innovation. Other studies have found out that research collaboration with universities result in positive impact on product innovations (Aschhoff & Schmidt, 2008; Eom & Lee, 2010). More recently, Maietta (2015) argued that collaboration with universities in the low-tech industry have a stronger impact on process innovation than product innovation. Similar results were found where university research collaboration has a positive impact on product (Un et al., 2010) and process innovation (Un & Asakawa, 2015). In light of this literature, the following hypothesis can be formulated:

Hypothesis 2: Collaboration between firms and universities will result in a higher propensity to innovate

4.2.3 Cross-functional teams and innovation performance

Apart from OI and collaboration practices, there are other organizational practices a firm can use to enhance its propensity to innovate. One of these practices is the implementation of cross-functional teams (CFT), which has been the subject of many studies in recent years (Bai, Feng, Yue, & Feng, 2017; Enz & Lambert, 2012; K. Lee & Ahn, 2018). According to Bunduchi (2009), creativity is an integral part of CFT and this can lead to increased innovativeness in new product development (NPD). In fact, creativity can lead to value creation. For instance, Enz and Lambert (2012) found that CFT can lead to value creation. This can be explained by the fact that these teams can combine different sources of information to create new knowledge. Moreover, CFT increase innovation performance of functionally organized projects (Blindenbach-Driessen, 2014) because they contribute to tacit and explicit knowledge sharing (Z. Wang & Wang, 2012). Finally, K. Lee and Ahn (2018) also demonstrated a positive impact of adopting CFT and OI practices. For these reasons, this hypothesis can be stated:

Hypothesis 3: *The adoption of CFT activities will result in a higher propensity to innovate*

4.2.4 Outsourcing and innovation performance

Many scholars discussed that networking with partners have provided a positive and significant effect on innovation performance (Nieto & Rodríguez, 2011). In fact, it is becoming common for firms to interact with different actors dispersed across the world in order to increase their innovation potential (Narula & Zanfei, 2005). One example of cooperation through networking is a firm’s decision to outsource some activities to other companies, whether locally or internationally. According to Lewin, Massini, and Peeters (2009), outsourcing is way for companies to gain access to new sources of knowledges. When companies outsource some of their activities to a low-wage country, it reduces their costs of production and lower wages of onshore researchers (Glass & Saggi, 2001). This can result in cheaper innovation, which can incentivize firms to increase their investments in innovation resulting in new and improved products. This aspect has been demonstrated in an empirical research amongst UK firms, in which international outsourcing helped companies innovate more frequently (Criscuolo, Narula, & Verspagen, 2005). Moreover, firms deciding to outsource R&D activities can reap many benefits through access to more diverse sources of information (Paju, 2007), highly qualified labour (Kedia & Mukherjee, 2009; Lewin et al., 2009) and new technologies (Maskell, Pedersen, Petersen, & Dick-Nielsen, 2007). Based on these reasons, the following hypothesis can be derived:

Hypothesis 4: *Outsourcing activities will result in a higher propensity to innovate*

4.2.5 Technology adoption and innovation performance

As previously mentioned, SCT adoption has benefits that can be directly related to firm performance. According to Thun (2010), the adoption of SCT can help enhance a firm’s delivery performance because it plays an important role in information sharing across supply chains. This will result in increased information visibility and data accuracy by the other actors and partners of the supply chain, which will enable a better response time (Sambamurthy, Bharadwaj, & Grover, 2003; Thun, 2010). In particular, data accuracy is directly correlated to inventory accuracy, which is expected to rise with information sharing (Heese, 2007). With better inventory control, a firm’s performance will increase through better delivery times. As was previously mentioned, the supply chain actors must have complementarity in their technological choices. Because SCT adoption transcends an organization boundary (Saldanha et al., 2015), an effective implementation is strongly tied to information sharing and visibility systems used in collaboration with supply chain partners. High visibility coupled with information sharing in the supply chain increase connectivity which results in better coordination across the supply chain networks (Fawcett, Osterhaus, Magnan, Brau, & McCarter, 2007). Delivery performance is enhanced as a result of faster decision-making (Cachon & Fisher, 2000). Furthermore, Setia and Patel (2013) argue that delivery performance can also be enhanced through SCT adoption because it increases a firm's knowledge capability and absorptive capacity. This knowledge comes from the different tools adopted such as a demand planning tool or CRM which allows executives to quickly monitor customer behaviours in real-time and adapt their strategy (Fawcett et al., 2011). This quick adaptation to customers' demands allows better delivery performance and increase order and product flow (Kosansky & Schaefer, 2008). Finally, when data on customers and stock management is frequently shared in real-time, it allows to better predict the customer demand and improve delivery times (Seidmann & Sundararajan, 1997). SCTs are typically used in combination with an ERP to increase performance. As was previously mentioned, there are multiple technologies that can help bring benefits to different parts of the supply chain. It is expected that a high number of these technologies together will result a higher propensity to innovate through better firm performance.

Hypothesis 5a: *The higher the number of supply chain technologies adopted, the higher the propensity to innovate*

Similarly, advanced BI&A technologies have become part of complex products and play a key role in productivity improvement (Breur, 2015; M. E. Porter & Heppelmann, 2014). These technologies also provide a potential competitive advantage to organizations able to profit from all of the data generated (M. E. Porter & Heppelmann, 2015). Schniederjans and Hales (2016) argued that the adoption of SaaS plays a role in improving economic performance. Through improvements of a firm's economic performance, it can be expected to see more investments in the creating of new products and processes, leading directly to increased innovation performance. BI&A technologies help create products and services that are adapted to their customers. Dynamic interactions between a firm and its customers provide the opportunity and flexibility to adapt to their needs (Bantau & Rayburn, 2016; Kumar et al., 2013). For these reasons, the following hypothesis can be derived:

Hypothesis 5b: *The higher the number of BI&A technologies adopted, the higher the propensity to innovate*

Product customization is made possible by AMTs. A specific combination of these technologies can provide a competitive advantage to firms that can't be transferred to other companies (Milgrom & Roberts, 1995; Stoneman & Kwon, 1994), suggesting that more than one technology should be adopted. Niaki and Nonino (2017) emphasize on the economic benefits of AM specifically by decreasing inventory turnover and increasing flexibility. Furthermore, the propensity to innovate may be increased as a consequence of AM adoption (Niaki & Nonino, 2017). AMTs can even improve productivity when doing manufacturing at a large-scale (Ituarte et al., 2016), which can increase firm performance in return. Based on these reasons, the following hypothesis can be derived:

Hypothesis 5c: *The higher the number of AMTs adopted, the higher the propensity to innovate*

4.2.6 Other factors and control variables

Apart from all the factors that were previously mentioned, other variables can also impact innovation performance. These factors include the age of the firm, its size, its R&D expenditures or the industry in which it operates. This paragraph will briefly discuss how these characteristics can have an impact on innovation performance. These factors will be used as control variables in the regressions.

In terms of size of the firm, the literature already presented its positive impact on innovation performance (W. M. Cohen, 1995) because larger firms have more resources to develop innovations (M. Rogers, 2004). In fact, large firms have a higher probability to have slack resources that can be used for other projects outside the core activities (Nohria & Gulati, 1996). For instance, slack in human resources can enable the creation of a team that will be focussed on collaborating with external partners (Beckman, Haunschild, & Phillips, 2004).

Age can also impact innovation performance. In a similar logic to the effect of size, older firms are more likely to have slack resources compared to younger firms (Penrose, 2009). However, some studies found that older firms see their innovation quality decreased (Balasubramanian & Lee, 2008). In fact, as companies age, their core activities and organizational structure doesn't change much because they have already their main resources and customers to serve (Hannan, Hannan, Pólos, & Carroll, 2007; Ranger-Moore, 1997). Consequently, firms tend to see a decrease in their innovation performance as they age. In fact, according to Klepper (1996), while maturing, firms tend to become less innovative. These findings are also supported by empirical data. For instance, Huergo and Jaumandreu (2004) found that age was inversely correlated to the probability of innovation amongst 2300 manufacturing firms in Spain. Hansen (1992) found similar relationship, supporting that innovation performance decreases as firms age.

Based on the R&D lab model with inputs and outputs, it is expected that R&D will have a positive outcome on innovation performance (Brown & Svenson, 1988). A firm investing in R&D will have a higher probability of leading to process and product innovations (W. M. Cohen & Levinthal, 1989). For instance, W. M. Cohen and Levinthal (1989) argued that firms invest in R&D not only to stimulate innovation, but also to develop and maintain their capacity to absorb new knowledge.

Furthermore, there are other factors on which firm needs to focus in the context of sustainable innovations (Hossain, 2013; Nyström & Mustaquim, 2014). These factors refer to the requirements of Sustainable Development which are outlined by customers, governments and other groups (Ketata, Sofka, & Grimpe, 2015; Tsai & Liao, 2017). As a consequence, firms are forced to redesign their products and services in order to meet these requirements.

4.2.7 Proposition of technology bundles

The propositions that will be presented in this section constitute an attempt at categorizing technologies into smaller groups in order to predict some of the association rules that can be expected. This analysis does not constitute a hypothesis and needs to be taken with a pinch of salt. The propositions are elaborated based on the review of technologies presented in Chapter 3. Each technology has a specific role it can play in a firm. For example, a WMS and CRM play similar roles but adapted to the objectives of a business unit. Both tools are a database that integrates information on products and customers respectively. Because both technologies are similar, it makes sense to classify them in the same subgroup of technologies. This is what this section aims to achieve: finding smaller groups of technologies so that a general pattern of technologies adopted can be predicted or expected when the associations will be computed. All families of technologies have a proposition for the expected pattern to be found, except for BI technologies, because there are only five of them.

Material Handling and Supply Chain Technologies

While it may be difficult to predict the exact technology bundles that will result of the analysis, an attempt to have an idea based on the role each advanced tool can play in a firm's core activities can be presented. Each technology has been explained in Chapter 3. Analyzing Figure 3.3, the different MHSCL technologies and how they relate to each function within a firm can be observed. There are three particular aspects that can help categorize technologies. First, there are the tools that are important to run the business from finding customers to buying materials and distributing end products. Amongst the most popular bundles, it is expected to find technologies such as CRM, TMS and WMS because they are important to run the business by managing customers demand, stock materials and transportation of end products. As was previously mentioned, some firms might prefer to use only one or two of these tools because of budget constraints or because they simply don't have enough data that needs to be managed by a software. The second aspect is related to planning and collaboration with suppliers and includes two technologies: SCCVS and DF/DP. SCCVS gives visibility to all supply chain partners while DF/DP allows better planning for material purchases and customer demands. Finally, the last set of technologies is related to tracking and includes AS/RS, QR, RFID. While it is known from the literature that firms are mostly using QR, it will be uncommon to see QR and RFID adopted together. Based on these insights, a proposition can be made regarding the general bundle to be adopted by firms:

Proposition 1: *{CRM, TMS, WMS} + {SCCVS, DF/DP} + {QR/RFID, AS/RS}*

Business Intelligence Technologies

Figure 3.6 shows the five BI technologies that are explored in this study. SaaS is the core technology within this family because it allows all other software to be used in the cloud, which means without the need to be installed and maintained by the firm. SaaS tools are sold by software service providers that charge a monthly subscription fee. It is anticipated to see this technology in most, if not all bundles. The other technologies will be based on how advanced a firm's data capabilities is. For example, ED provides a high-level view to executives, while RTM allows the monitoring of data in real-time. It is expected to have a combination of these technologies with the core being SaaS. As for BDS, it is not believed that it will not be very popular in bundles because the survey collection period dates back to 2015. Some of the popular bundles will also include IaaS as most companies providing SaaS will be required to have IaaS to host their software. Because BI technologies are so intertwined, no proposition will be suggested as to patterns that will emerge from this analysis.

Design and Information Control Technologies

Figure 3.11 shows the different DIC technologies that can be adopted by firms. These technologies can be divided into four main categories: product design, quality assurance, planning and communications. The first three categories are mostly comprised of software that will help run a manufacturing firm. For instance, product design tools include VPD, VM that allow engineers to design the product in the best possible way before sending it the prototyping or the manufacturing phase. Quality assurance relates to a software that will inspect products during and after they are processed. Tools such as UAS and ASI are included. To plan the materials needed and how to operate the machinery when the manufacturing starts, many types of software are needed. These include ERP, MRP II, MES and CIM. For instance, MRP II allows to plan the materials needed to manufacture a product. An ERP is a tool that integrates many different business units within a firm to allow for better planning and control over what is produced. Finally, the last category is comprised of communications technologies such as EDI, WSN and WCP. While these technologies can be important to transfer data within a company or with its partners, they're also important to do quality checks on the products as well as ensuring the security of the employees working in a factory. Due to the high number of technologies available and required, many different bundles that would have four or five technologies adopted are expected to be found in the results. It is expected to find bundles that could contain at least one technology of each category as follows:

Proposition 2: *{VPD, VPM} + {ERP, MRPII, MES, CIM} + {WSN, EDI, WCP} + {UAS, ASI}*

Processing and Fabrication Technologies

Figure 3.12 shows all technologies related to DIC and PF together in one diagram. Focussing only on the PF technologies, a few categories that allows to group some technologies together can be noted. First, there are technologies that focus on controlling the machinery and adding flexibility to the production process. These include CNC, FMS/FMC and are responsible for scaling up massive production needs. Second, there are technologies that inspect products or transport them which include AMST and robots with and without sensing. At least one of these technologies will ultimately be adopted by most firms it can be expected to see it as part of many bundles. The last set of tools is in fact different advanced processing technologies that include PS, MM, MEMS, LSR and additive manufacturing technologies (i.e. 3DP, 3DM, 3DO). These technologies are expected to be adopted by a small number of firms, which means that they are not expected to be regrouped in bundles. In general, some niche companies will have adopted 3D printing because it has become cheaper and faster to design prototypes. However, more specialized firms could have adopted a specific type of advanced manufacturing such as MEMS and MM. Because of the advanced nature of these technologies, results are not expected to show a lot of combinations within the last category (PS, MM, MEMS and LSR). Considering that the year 2014 was the beginning on Industry 4.0, only pioneers will be using these complex technologies. For these reasons, the following pattern of advanced PF technologies can be proposed:

Proposition 3: *{CNC, FMS/FMC} + {AMST, ROBOT(s)} + {PS, MM, MEMS, LSR, 3DP/3DM/3DO}*

These propositions are based on the review in Chapter 3 related to the functionality of each technology. The main reason for attempting to dividing each family of technology into subgroups is to enable a more practical interpretation of the resulting bundles of technologies that will be generated with the different algorithms. The next section focusses on the objectives of the research and the different methodologies that will be applied in order to attain these objectives.

4.3 Research Objectives

4.3.1 General objective

The general objective of this study is to investigate the Canadian context of the adoption of advanced technologies and their impact on the propensity to innovate. Different methodologies are used in order to explore these different factors, including the adoption of collaboration strategies. Once the impact of technologies is better understood, the main goal of this thesis is to characterize technology adoption by understanding the complementarities between advanced technologies. The next section enumerates the specific objectives related to this study.

4.3.2 Specific objectives:

1. Understand the factors that impact the number of technologies adopted;
2. Measure the joint impact of adopting advanced technologies and using OI practices on the propensity to innovate;

3. Portrait the technologies adopted by Canadian firms by finding the most frequently adopted bundles by category of technologies;
4. Create a network view of bundles of technologies adopted by Canadian firms by category of technologies;
5. Understand the dynamics of technology adoption based on the time they have been adopted;
6. Compare the adoption strategies by firms characteristics such age, size and industry and revenue;
7. Propose management and business implications for the promotion adopting emerging technologies.

4.4 Research Methodology

This section will provide a description of the research methodology proposed to reach the different objectives listed above and to validate the hypotheses of this study. To attain objectives (1) and (2) presented above, an econometric model will be used where the number of technologies adopted is considered endogenous. A number of hypotheses were developed to validate the impact of adopted technologies and OI strategies on the propensity to innovate. Objectives (3) and (4) will be validated by using a Market Basket Analysis (MBA) that allows to find common bundles of technologies adopted by firms. Based on the survey of technologies presented in Chapter 3, a series of propositions will be suggested regarding which bundles of technologies should be expected to be adopted by firms. Finally, to reach objectives (5) and (6), an algorithm will be used to identify the order in which technologies have been adopted by firms. These different analyses will contribute to attain the last objective (7) that aims to provide business recommendations stemming from the results. The next few paragraphs will present the data used as well as the different methods employed to reach these objectives.

4.4.1 Data Collection

The Survey of Advanced Technologies (SAT 2014) conducted by Statistics Canada in 2015 is the main data source for this research. This survey contributes to all the objectives specified above. It is the most recent survey that covers an exhaustive view on emerging technology adoption behaviours by Canadian firms. The target population consisted of all firms with at least 10 employees and at least 250,000$ in revenues in the following sectors: Forestry and Logging (NAICS 113), Mining, Quarrying, and Oil and Gas Extraction (NAICS 21), Utilities (NAICS 22), Manufacturing (NAICS 31-33), Wholesale Trade (NAICS 41), Retail Trade (NAICS 44-45), Transportation and Warehousing (NAICS 48-49), and Professional, Scientific and Technical Services (NAICS 54). Initially, a stratified simple random sample of 11,887 enterprises was selected from the survey population of 84,322 enterprises on the September 2014 version of Statistics Canada Business Register (BR). The survey population was stratified by industrial grouping, region and three size classes based on the number of employees per firm:

- Small firms (10 to 99 employees)
- Medium-sized firms (100 to 249 employees)
- Large firms (more than 249 employees).

Data collection was done in 2015 between February 25th and June 25th. Data was collected directly from survey respondents with enough knowledge on the firm and advanced technologies (i.e. entrepreneur, CEO or senior manager). Responding was mandatory through the Statistics Act in Canada. This is one of the main reasons why this research uses a Statistics Canada survey (instead of a custom survey). Because of the Statistics Act, a high response rate was obtained and it is more convenient to ensure generalization of the results. A file of weighted micro data was available for all sampled firms in the survey population for which data were reported or imputed. Weights were adjusted by a factor to ensure the final estimates were representative of the entire survey population. The overall response rate of the survey was 68.8% for a total of 7,912 completed questionnaires. The list of variables used is summarized in Table 4.2. One of the drawbacks of using this survey is that this research had to be adapted to the type of information that was collected. For example, the only OI practice that is measured is collaboration and strategic alliances with firms, governments or universities. While conducting a custom survey could have allowed to add more open innovation measures, the choice of using SAT 2014 was made because of its representability of Canadian firms.

In order to add control variables to this study, Statistics Canada linked the survey with other data sources such as the Business Register (BR) and the General Index of Financial Information (GIFI) data. Joining several sources of data was necessary to gain information about size, age as well as R&D expenditures of the firms surveyed in SAT 2014. For instance, the BR is Statistic Canada's central database of baseline information on all businesses and institutions operating in Canada. The repository is maintained continuously and can provide related attributes required for survey sampling frames and stratification amongst other things. On the other hand, the GIFI is a standard list of codes that are used by firms to prepare their financial statements. This database contains all the variables related to a corporation's tax returns reports, which includes operating expenses, gross profit/loss, assets, liabilities, etc. Finally, Statistics Canada also linked the survey with the Longitudinal Employment Analysis Program (LEAP), which contains employment information on all Canadian businesses, starting with the 1983 reference year. This was used to calculate the age of each company participating in the survey. These complementary variables are described below.

The survey is divided into four main families or categories of advanced technologies:

1. Material handling and supply chain and logistic;
2. Business intelligence;
3. Design and information control;
4. Processing and fabrication.

- Each category contains between 5 and 12 technologies that firms had to select from. The complete list of technologies was presented above in Table 3.1. An index of these technologies was built. The survey comprises a set of multiple-choice questions regarding the adoption of specific advanced technologies. For each technology, the respondent had to choose one of four answer categories about the experience in using the said technology: No plan to use, Plan to use within two years; Have used for three years or less; or Have used for more than three years. An example of the first question on technology adoption is presented in Table 4.1.

Table 4.1: Example of technology adoption question in SAT 2014

Does your enterprise use or plan to use any of the following Advanced Material Handling, Supply Chain and Logistics Technologies?		
Type of technology	Category	Code
b) Customer Relationship Management (CRM) software c) Software for demand forecasting or demand planning d) Transportation management system e) etc.	▪ No plan to use ▪ Plan to use within two years ▪ Have used for three years or less ▪ Have used for more than three years	0 1 2 3

- To construct the index of adopted technologies, a binary variable was created to separate between firms who adopted and firms who did not adopt. Codes 2 and 3 were recoded to take the value 1 while codes 0 and 1 were recorded as 0. The decision not to include firms that plan to use a technology within two years related to the uncertainty of adoption. While firms that didn't plan to use a technology might do so because it is not relevant to their sector or because they do not have enough capital, the same could happen to firms that plan to adopt a technology today but often change their mind later on. Because there is no way to mitigate this uncertainty, the choice was taken to only study firms that have already adopted a technology. Therefore, the index of adopted technologies consists of the sum of technologies that each firm had adopted in the past (hence coded 2 or 3). A natural logarithm was then applied to the index[9]. The index of adopted technologies was calculated as follows:

$$Index_{Technologies} = T_1 + T_2 + \cdots + M_n$$

[9] The natural logarithm of this index was used for the regression analysis to ensure the normality of the variable. This will be explained later in this chapter.

Where T_n is equal to 1 if a technology has been adopted, and 0 if not. The number of technologies n is dependent on the category of technologies: Material Handling, Supply Chain and Logistics contain eight technologies; Business Intelligence contains five technologies; Design and Information control contain 12 technologies; Processing and Fabrication contain 12 technologies.

- The same method was applied to the variable representing the measures adopted by firms to counter obstacles that may slow down the adoption of each specific category of technology. The respondents could answer this question only in the case they had at least one in-use technology. For each measure, the respondent had to choose whether it was adopted (code 1) or not (code 0). An enterprise may choose to adopt multiple measures. The index was created by summing the number of measures adopted regarding each of the technologies[9]. The measures included in the survey are the following: (1) performance bonuses; (2) improved working conditions (e.g. flexible hours, health and safety); (3) college and university recruitment; (4) offer training as needed for the needs of the organization; (5) calling in consultants or subcontracting for short-term needs; (6) collaborating with universities or research centres to develop advanced technologies; (7) collaborating with other enterprise(s) or client(s); (8) acquiring another enterprise that had already developed the required advanced technology; (9) seeking government support (e.g., technical, financial); (10) seeking support from professional organizations. The index of the measures adopted was calculated as follows:

$$Index_{Measures} = M_1 + M_2 + \cdots + M_{10}$$

Where M_n is equal to 1 if the measure has been adopted, and 0 if not.

- All the variables regarding open innovation and collaboration practices are binary variables that did not need to be recoded. These cover topics such as OI strategies, including collaboration with firms, with universities and with governments; outsourcing. The literature has demonstrated the importance these variables play in increasing the propensity to innovate. Using OI practices increases the propensity of developing radical innovation through the recombination of external knowledge and experience acquired (Shi & Zhang, 2018).

- The other factors variables are binary and did not need to be recoded. These variables cover product development strategies (e.g. cross-functional teams and concurrent engineering), other management practices (e.g. product data management and life cycle management) and outsourcing. It is thought that these practices can also impact the propensity to innovate. For instance, cross-functional teams have been demonstrated to play a role in increased innovativeness specifically in product development (Bunduchi, 2009; Jugend & da Silva, 2012). Furthermore, outsourcing is becoming a common strategy allowing firms to interact with actors from all over the world, which was shown to increase the propensity to innovate (Narula & Zanfei, 2005).
- A variable of employee recruitment pertaining to the adoption of technologies was used as an instrument to understand technology adoption. The reason behind this is that companies who decide to recruit employees with the knowledge to use advanced technologies may be more likely to adopt them. This is also similar to some of the measures discussed above, notably in the case of college and university recruitment as well as offering training based on organizational needs.
- Finally, the Capital Expenditures (CAPEX) variable used is a percentage of expenditures that is allocated to each family of technology. There is an interest in using this variable because of the cost involved in adopting advanced technologies and how it may impact technology adoption. For example, investments in BI technologies are important for companies because it helps them quickly understand and adapt to customers' needs by collecting and analyzing data, which can lead in an increased performance and competitive advantage (Park et al., 2017; Torres et al., 2018). Consequently, capital expenditures are an important factor that can influence technology adoption. This variable is constructed using the total amount of capital expenditures invested on all advanced technologies and multiplying it by the percentage breakdown relative to each category of advanced technologies:

$$CAPEX_n = Total\ investment \times \%\ Investment_n$$

Where *n* is the category of technology (e.g. MHSCL, BI, DIC and PF).

Table 4.2 shows the list of all variables that are used in this thesis. The control variables were constructed with other sources linked to the main survey. The size of the firm is represented by the natural logarithm of the number of employees of a firm. The age of the firm is constructed by subtracting the birth year of a company from a baseline year (e.g. 2016).

Table 4.2: Variables used in SAT 2014

Independent Variables	**Dependent Variables**
▪ Number of adopted technologies ▪ Measure to mitigate obstacles to adoption ▪ Capital Expenditures (CAPEX) ▪ Recruitment of new employees pertaining to the adoption of new technologies ▪ OI and collaboration practices (e.g. with firms, universities, government). ▪ Other factors: concurrent engineering, cross-functional teams and outsourcing. ▪ Control variables: size, age, industry	▪ Type of innovation ▪ Number of adopted technologies (endogenous)[10]

To explore the impact of industry on innovation propensity, this study uses a sector classification based on the Pavitt Taxonomy (Pavitt, 1984) that identified four groups of industries: Science-Based (SB), Specialized Suppliers (SS), Scale Intensive (SI) and Supplier Dominated (SD). This

[10] The number of adopted technologies appears as an independent and dependent variable because there are two stages to the econometric model used in which this variable is considered endogenous. The econometric model is explained in detail in section 4.4.2 below.

classification covers a large range of industries in the manufacturing sector. For instance, SB includes sectors that are based on R&D such as pharmaceutical and electronic industries that usually have an easy access to research institutions and universities. Because they highly rely on patents, they tend to collaborate more closely with public research institutes. Other industries that are part of the science-based sector is the aerospace parts and products sector.

SS include firms that produce new processes and products for other companies such as machinery and equipment (fitting in the advanced manufacturing tools). They focus mostly on product innovation and tend to cooperate with suppliers and customers. SI includes firms in the basic metals and automotive sectors where technological innovation is incremental. They mainly focus on process improvements by importing knowledge and science developed by their partners. Finally, SD includes traditional sectors such as textiles and food, which are largely composed of small firms that rely on suppliers to supply them with machinery and other equipment.

To consider all firms that are surveyed in SAT 2014, the classification needs to be extended to include service and knowledge-intensive firms. A revised Pavitt taxonomy included information-intensive (II) industries (Tidd, Bessant, & Pavitt, 2005; Tidd & Bessant, 2018). Other authors combined found no statistical difference between II and SI and decided to combine them into one common sector (Bogliacino & Pianta, 2016). However, the classification took in consideration the different approaches proposed in the literature and can be found in Table 4.3 with the corresponding NAICS codes for each category. The SD sector is split between resource-intensive and labour-intensive to keep food and textile manufacturing separately. Furthermore, the SI and service-intensive categories remain separate as well.

Table 4.3: Sector classification variables based on the OECD revised Pavitt taxonomy (1984)

Variable	Sector	Pavitt Sector	NAICS code
inress	Resource-intensive	SD	311, 312, 321, 322, 324, 327
inlab	Labour-intensive	SD	113, 313, 314, 315, 316, 332, 337, 339
inscal	Scale-intensive	SI	323, 325, 326, 331, 3361, 3362, 3363, 3365, 3366, 3367, 3368, 3369
inspec	Specialized suppliers	SS	333, 335
insci	Science-based	SB	334, 3364
inserv	Service-intensive	II	21, 22, 23, 41, 44, 48, 49, 51, 52, 53, 54

4.4.2 Econometric model

This first model aims at understanding what influences the propensity to innovate by validating hypotheses 1 to 5 that were previously developed, which aim to reach objectives (1) and (2) presented above. The reasons to examine the propensity to innovate are twofold. First, although the adoption of these technologies may not impact innovation performance directly, some of them may do because they facilitate specific activities, collaboration for instance, that leads to increased innovation and possibly improved economic performance at a later point. In addition, firms may have difficulty in adopting specific technologies, i.e. face obstacles to adoption. If the analysis shows that both adoption of advanced technologies, as well as obstacles to this adoption have a positive relationship with economic performance, the two effects will have to be disentangled. In a similar fashion as obstacles to innovation may have a positive effect on innovation performance (this positive relationship paradox has been interpreted in the literature as an indication of how successfully firms can overcome these obstacles, see for instance (J. Baldwin & Lin, 2002; Tourigny & Le, 2004)), this thesis aims to investigate whether obstacles to adoption (and/or the measures adopted to counter these obstacles) may follow a similar pattern because firms invest in mitigating these factors. A test of endogeneity is then performed to validate the endogenous effect technology adoption may have on innovation performance. This will be further explained in the results section. The models presented below therefore start with this first model of the impact of obstacles to adoption on innovation performance while taking into consideration the mitigating effect of specific actions on obstacles to adoption.

Using SAT 2014, the factors that influence the propensity to innovate (Innov), in particular the impact of advanced technology adoption and OI practices are estimated. For this purpose, a simple logit or probit regression will be used:

$$\ln\left(\frac{P(Y_{1i}=1)}{P(Y_{1i}=0)}\right) = X_{1i}\beta_1 + X_{2i}\beta_2 + \epsilon \tag{1}$$

$$\Phi^{-1}[P(Y_{1i}=1)] = X_{1i}\beta_1 + X_{2i}\beta_2 + \epsilon \tag{2}$$

where Φ is the commonly used standard normal distribution function.

The obstacles that may slow down or prevent the adoption of advanced and ICT technologies are simultaneously determined with the decision to adopt a technology or not, and the latter is potentially endogenous. A more appropriate regression model consists in using instrumental variables where the adoption of these technologies is endogenous. The Instrumental-Variable Probit Regression (IVPR) model to be used for this purpose is presented below:

$$Innov_{1i} = Y_{1i}^{*} = X_{1i}\beta_1 + Y_{2i}\beta_2 + X_{3i}\beta_3 + \epsilon_1 \tag{3}$$

$$Adopt_{2i} = Y_{2i} = X_{2i}\gamma_2 + X_{3i}\gamma_3 + \mu_1 \tag{4}$$

where it is observed

$$Y_{1i} = \begin{cases} 0 & if\ Y_{1i}^{*} < 0 \\ 1 & if\ Y_{1i}^{*} \geq 0 \end{cases} \tag{5}$$

and where Y_1 measures whether a firm innovates or not, while Y_2 represents the adoption of advanced technologies, which will be a continuous variable (the natural logarithm of the number of advanced technologies adopted); the index i represents the family of technologies adopted; and,

where X_1 is a vector of exogenous variables, X_3 is a vector of control variables such as the size or the sector of the firm, and X_2 is a vector of instrumental variables that has an effect on the adoption of advanced technologies (Y_2 being endogenous). The reason for using four separate models for technology adoption is twofold. First, the instruments used are not the same, particularly for the CAPEX variable. The survey measures it as a percentage spent by each family of technologies. Second, the DIC and PF families use the same CAPEX variable, as well as the same question for the measures to mitigate obstacles, which means both of these categories could have been combined to form only one model. However, because the list of technologies was so different, the choice was made to keep them separate.

More specifically, X_1 includes variables on OI strategies, product development practices and other factors that may influence innovation. These variables have been used to define the hypothesis stated above.

X_2 includes the instrument variables that are thought to be impacting the adoption of technologies. SAT 2014 measures the mitigating factors to reduce obstacles to the adoption of these technologies. This information provides an excellent basis to build one of the instrumental variables of the model. The selection of these variables was based on the two of the three determinants of technology adoption that were discussed in Chapter 2. Beside being impacted by technology-related factors, such as complexity and relative advantage, technology adoption can also be influenced by firms-related factors. These factors include absorptive capacity which refers to a firm's ability to integrate external knowledge (W. M. Cohen & Levinthal, 1990). For instance, identifying new technological trends and fields requires prior technological knowledge (K. Z. Zhou, Yim, & Tse, 2005), which further facilitates the integration of new technologies (Narasimhan et al., 2006). When new technologies are integrated, companies need to actively have a strategy to memorize new knowledge to avoid losing it (Johnson, Sohi, & Grewal, 2004; Moorman & Miner, 1997). Knowledge retention may be achieved by maintaining and reactivating integrated knowledge (Lane et al., 2006; Marsh & Stock, 2006). It can be argued that this assimilated knowledge needs to be reactivated through experience (Nonaka, 1994). There are a few mitigating measures that can account for experience to maintain knowledge in SAT 2014. For example, college and university recruitment and offering training as needed to employees can constitute experience that will increase the likelihood of absorbing knowledge from new technologies and maintain it. Similarly, the recruitment of new employees pertaining to the adoption of advanced technologies is also expected to help with the said adoption. Because companies may adopt more than one technology, assimilated knowledge becomes cumulative by nature. Prior knowledge in specific fields can help an enterprise maintain knowledge in related fields (Garud & Nayyar, 1994). In theory, recruiting employees with the right skills should help firms increase their degree of technology orientation. Consequently, a high degree of technology orientation in a company will result in larger technology portfolios (K. Z. Zhou et al., 2005). Because many measures to mitigate the obstacle to adoption of technologies tend to increase absorptive capacity amongst other things, the higher number of measures adopted should lead to a higher number of technologies adopted. Similarly, recruiting employees pertaining to the adoption of these technologies should also increase the technology portfolio of a firm, which why it can be used as an instrument in this case. Furthermore, companies need capital to be able to purchase these technologies. The amount of capital expenditures (CAPEX) can be an important instrument. These three instruments combined are expected to have an effect on the total number of technologies adopted.

X_3 will include control variables such as size, age and industry. The control variables will be composed of data from various sources such as the LEAP and GIFI databases to get information of the number of employees and financial data respectively. All the different variables used in this model have been summarized in Table 4.4.

The different models are tested in STATA using the *ivprobit* command. The dependant variable will be measuring the propensity to innovate using the type of innovation that a firm introduced. The survey provides information on whether a firm has introduced a new product, process, marketing or organizational innovation. The economic model calculates the probability of introduced said innovation, based on the different types mentioned previously. Innovation is defined according to the OECD guidelines and regroups four types of innovation (product, process, marketing and organizational) as previously mentioned in the survey of the literature (OECD, 2005). These four types of innovation are then grouped into technological innovation (processes, products) and non-technological innovation (organizational and marketing) (Mothe & Nguyen-Thi, 2010, 2012; Schmidt & Rammer, 2007). Non-technological innovation has also been recently amended by the OECD to include new processes (OECD & Eurostat, 2019).

The survey used in this study focusses on Canadian firms within the manufacturing and service industries. Different types of innovations can be found in both industries. For instance, high-tech manufacturing firms are known for their product innovations by relying more on in-house R&D and collaboration with universities whereas service firms are more likely to collaborate with customers and suppliers (Ada Leiponen, 2000; Mansury & Love, 2008). Non-technological innovations, such as marketing and organization, can be found in both industries (Flikkema, Jansen, & Van Der Sluis, 2007) but are more prominent in the services sector in the form of management or cooperation practices (Tether, 2005). Furthermore, organizational innovation in particular is more likely to be found in service firms (Mansury & Love, 2008; Tether, 2005; Tether & Tajar, 2008). One particular example of this type of innovation is external relationship innovation, which consists in developing relationships with external partners (Drejer, 2004). This can result in service firms engaging in collaboration with external actors. When it comes to marketing innovation, it is often used by firms that have lower R&D intensity as a strategy to increase their competitiveness and distribution channels (Hall & Bagchi-Sen, 2007), which relates mostly to service firms.

However, it is not advised to do a simple generalization in terms of type of innovation in the service sector (Evangelista, 2000). Moreover, some studies argued that there is a heterogeneity that can be observed when services are concerned (Camacho & Rodriguez, 2008). In other words, some services have more similarities with manufacturing firms than with other services (Preissl, 2000). This diversity in the service sector has been demonstrated in the literature (Camacho & Rodriguez, 2008; Miozzo & Soete, 2001; Tether, 2003). Furthermore, studies have shown that the service industry follow similar patterns to the manufacturing sector when it comes to innovation (Arvanitis, 2008; James H Love & Mansury, 2007). This supports the idea of heterogeneity within each sector, suggesting that the type of innovation can vary based on a firm’s core activities.

In total 8 different models will be tested according to the type of innovation: all four types combined, technological, non-technological, product, process, organizational, marketing, and business process (i.e. process, organizational, marketing).

Table 4.4: Summary of all variables used in the econometric model

Variable	Description	Name	Type
	Propensity to innovate variables		
Y_1	Any of type of innovation	allinno	Dependant
	Product	prodinno	
	Process	procinno	
	Marketing	markinno	
	Organizational	orginno	
	Technological	businno	
	Non-Technological	techinno	
	Business Process	nontechinno	
	Number of adopted technologies (1 index for each family of technology)		
Y_2	Material Handling, Supply Chain and Logistics	Index_MHSCL	Dependant (endogenous)
	Business Intelligence	Index_BI	
	Design and Information Control	Index_DIC	
	Processing and Fabrication	Index_PF	
	Explanatory variables impacting the propensity to innovate (Y_1)		
X_1	Collaboration and strategic alliances with universities and/or governments	Collab-uni&gvt	Exogenous
	Collaboration and strategic alliances with other firms	Collab-firms	
	Concurrent Engineering	Concurrent Eng.	
	Cross-functional teams	Cross-funct. Teams	
	Outsourcing in or outside Canada	Outsourcing	
	Competitive technology intelligence or benchmarking	CTI-Benchmarking	
	Sustainable development activities	Sustain. Dev-ESP	
	Product Development Management	PDM & LCM	

Table 4.4: Summary of all variables used in the econometric model (con’td and end)

X_2	List of instruments impacting the number of adopted technologies (Y_2)		
	Index of the number of measures used;	ln_Index_Measures	Instruments
	Capital Expenditures[11]	CAPEX	
	Employee Recruitment (dummy)	Empl Recruit	
X_3	List of control variables		
	Size	ln_size	Control Variables
	Age	ln_age	
	Industry	See Table 4.3	

4.4.3 Association rules mining

In the previous section, the technologies adopted were simply counted and built into an index. However, the combination of these technologies, and how firm adopt them in an “à la carte” framework is of interest, especially as a contrast with the traditional “one-size fits all” ERP. This method aims to reach objectives (3) and (4) to validate propositions (1), (2), (3) presented above. Because there is an interest in the combination of technologies and in their impact on firm innovation, a classic market basket analysis (MBA), also known as association rules mining, provides a tool that can easily be adapted to the data available. MBA first originated in the field of marketing to find complementarities between a group of products. Its first use seems to date back to 1993 when Agrawal et al. used it to study association rules between different products consumers would buy. MBA is a data-mining technique that has the main advantage of bridging the gap between macro and micro levels (Aguinis, Forcum, & Joo, 2013). For instance, association rules can provide information on the general behaviour of customers, but it can also be useful for micro

[11] CAPEX is a variable that is different for each family of technologies, which is one of the reasons why three different models were used.

analyses that look at segmenting customers and their buying patterns. In other words, it is a classification method that tries to find different combinations of items that are purchased together.

According to Cascio and Aguinis (2008), MBA can also bridge the knowledge gap between academics and practitioners. Berry and Linoff (2004) discussed a practical implication of an MBA analysis used to understand consumer behaviour when they purchase items on Amazon. In the case of Amazon, MBA is employed as a classification method that can help consumers see what items are bought frequently together. In addition to being used on consumer data, MBA can also be utilized on survey data. For instance, this technique has been used to discover that certain food allergens occur together following a survey asking which food allergens people had (Kanagawa, Matsumoto, Koike, & Imamura, 2009). Another example consisted in establishing the characteristics of students choosing to use counselling services versus those who chose not to (Goh & Ang, 2007). The methodology was originally developed to be adopted with binary data. There many algorithms that have been proposed in the literature to mine association rules. The first one that was efficient is *apriori* (Agarwal & Srikant, 1994). Other algorithms have been proposed to to improve computational efficiency such as: *partition* (Savasere, Omiecinski, & Navathe, 1995), *sampling* (Toivonen, 1996), *FP-Growth* (Han, Karypis, & Kumar, 2000) or e*clat* (Zaki & Gouda, 2003). The same results can be obtained with these algorithms, but *apriori* was the one that was selected because of its rapid performance on a sparse database with R.

The format that was initially available in the Statistics Canada survey can be found in Table 4.5. The first step was to transform this data to binary format. As previously mentioned, the categories with a code of 2 and 3 together had to be combined (refer to Table 4.1). In other words, codes 2 and 3 will be recoded to 1 and all the rest will be coded to 0. This ensures that only firms that have already adopted a technology at the time of the survey are considered.

Table 4.5: Format of data in SAT 2014

Company	Q1a	Q1b	Q1c	Q1d	Q1e
Firm 1	0	2	3	1	0
Firm 2	1	1	1	0	0
Firm 3	2	0	0	0	1
Firm 4	3	2	1	1	1
Firm 5	1	1	1	0	0

Up to this stage, everything that was done to clean the variables and recode the data has been computed in STATA. However, the data needed to be converted into transactions which is the preferred format to mine for association rules. The transaction class in R contains information in binary form about the technologies adopted. It contains other types of information regarding the frequency of adoption of each technology as well as the number of technologies adopted. The following code is an example that summarizes the information contained in a transaction class:

```
summary(Q1.tr)
transactions as itemMatrix in sparse format with
3520 rows (elements/itemsets/transactions) and
8 columns (items) and a density of 0.3038707

most frequent items:
a       d       g       b       c (Other)
1608    1552    1447    1277    1029    1644

element (itemset/transaction) length distribution:
sizes
1    2    3    4    5
1270  830  542  389  489

Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
1.000   1.000   2.000   2.431   3.000   5.000

includes extended item information - examples:
labels
1      a
2      b
3      c
```

The information contained in the different rows representing each firm with their technology adoption behaviours is displayed in the summary above. It should be noted that the number of technologies adopted is represented by the element length distribution. For instance, two tables can be extracted from the code above: Table 4.6 displaying the most frequent technologies found in the rules and Table 4.7 showing the length of the rules or the number of technologies observed in each rule.

Table 4.6: Example of summary statistics on association rules - Most frequent items

Items	a	d	g	b	c	Other
Frequency	1608	1552	1447	1277	1029	1644

Table 4.7: Example of summary statistics on association rules - Length of rules

Length	1	2	3	4	5
Frequency	1270	830	542	389	489

For instance, it is possible to deduce from Table 4.7 that the maximum size of a transaction is five, which means that the maximum number of technologies being adopted together by a firm is five (489 in this case). However, the least popular size of transactions is four (389), which means that there are more firms that have adopted five technologies than those that have adopted four. Once the data is structured in this format, the *apriori* algorithm can be run.

Definitions

Let I = $\{i_1, i_2, i_3, \ldots\}$ be an item set, for example, I = {A, B, C} Each item set contains a list of items, or in this case, technologies that have been purchased (adopted). The data set will contain a maximum of 7912 item sets representing each firm and their technology adoption behaviour. In formal words, a transaction is a basket containing the technologies that a firm has adopted. The *apriori* algorithm will take the baskets from each firm and compute association rules according to the parameters set. A rule is denoted by R_1={A} => {B}. The former is a representation of having technology {B} in the same basket that contains technology {A}. This same rule is formed by an item set denoted {A, B}, which means that the basket contains technologies A and B. Each rule is formed of an antecedent (often denoted as Left-Hand Side (LHS)) and a consequent (often denoted as Right-Hand Side (RHS)). For example, in R_1, {A} is the antecedent and {B} is the consequent. The following paragraphs will define the measures used in the association rules.

Measures in association rules

The most used indexes in categorizing associations rules are the lift, the support and the confidence (Berry & Linoff, 2004; Larose, 2005; C. Zhang & Zhang, 2003) Lift is the first index that needs to be examined because it provides information on the existence of a rule (Aguinis et al., 2013). It is defined as:

$$Lift = \frac{P(A \cap B)}{P(A) \times P(B)} \tag{6}$$

In this study, A and B are two different technologies adopted. The numerator assumes that technology A and B are adopted together while the denominator assumes that each technology is adopted independently from the other. If the numerator is similar to the denominator, the ratio will be very close to 1.0 suggesting that the co-occurrence between technology A and B is a coincidence. If the lift is higher than 1.0, it indicates a positive relationship of complementarity between technologies A and B. In the other words, it means that A and B are positively correlated. On the other hand, a negative relationship will be shown by a lift lower than 1.0. In other words, adopting technology A will be reflected by not adopting technology B. Baralis, Cagliero, Cerquitelli, Garza, and Marchetti (2011) suggested filtering out all rules that have a lift close to 1.0. Therefore, the lift was used as a first indicator to reduce the number of rules and only study the ones that are interesting enough.

The second index of interest is the support and is defined as:

$$Support = P(A \cap B) \tag{7}$$

It ranges from 0 to 100% and indicates the probability of co-occurrence of technologies A and B. E. Cohen et al. (2001) argued that rich and large data sets can decrease the usefulness of the support index because support values will be low and similar. This noise is caused by the high number of different transactions or technology adoptions in this case. This makes it difficult to compare the strength of association rules based on the support indicator only.

Finally, the last index is the confidence and is defined by:

$$Confidence\ (A \rightarrow B) = \frac{P(A \cap B)}{P(A)} \tag{8}$$

While support reflects the frequency of adoption of technology A and B, the confidence is the probability that technology B is adopted considering that technology A is adopted. Contrary to support, confidence is independent of data richness and size because it only focusses on transactions where both technologies A and B have been adopted. In other words, confidence explains the probability that B is adopted if A is adopted. The index ranges from 0 to 100 percent and will be usually higher than the support for the same rule. Another advantage of the confidence index is that it can be used for building casual theories (Aguinis et al., 2013). In addition to the expression defined above, the confidence can also be calculated from technology B standpoint:

$$Confidence\ (B \rightarrow A) = \frac{P(A \cap B)}{P(B)} \tag{9}$$

This indicates the probability of adopting A if B has been adopted. Both expressions can be very different if there is a high delta between the probability of A and B separately (Gu et al., 2003). A high difference in the confidence of {A}=>{B} and the confidence of {B}=>{A} may be used to derive a casual hypothesis that one technology leads to another but not the other way around (Merceron & Yacef, 2003).

Practical implications of the *apriori* algorithm

There are multiple ways to interpret the rules generated. For instance, it is possible to find all the rules that have the business intelligence technology B as a consequent. Technology B is big data software (e.g., Hadoop) and could indicate which other technologies are complementary to it. This could help firms find out what technologies should be adopted with big data software, for example. For a provider of these technologies, association rules can give insight into which technologies should be sold together as a bundle. For a firm that's adopting these technologies, these rules can help provide the industry's best practices in terms of technology adoption. The complementarity between various technologies suggests the possibility to develop further the concept of technological proximity that was previously discussed in the literature review.

4.4.4 Frequent sequence mining

Similar to association rules mining, frequent sequence mining is used to identify patterns in an ordered item set. In standard grocery shopping, customers will tend to buy their items in a certain order, but these items will be bought at the same time. However, in technology adoption it should be noted that the order in which technologies are adopted can be important. For example, whether a firm adopts a business intelligence software to analyze data or install sensors that collect data first is not clear. Frequent sequence mining gives insight into these decisions because it allows to add temporality to an algorithm like *apriori*, which will answer objectives (5) and (6) presented above. To account for the adoption dynamics, the c*spade* algorithm will be used. It was originally developed by Rakesh Agrawal in 1995 (R. Agrawal & Srikant, 1995). At first, Srikant and Agrawal (1996) used the algorithm in retail industry. It was used to predict the likelihood of a customer purchasing a sequel to a book purchased previously. The algorithm was also used in other disciplines such as in biomedical and bioinformatics (Batal, Valizadegan, Cooper, & Hauskrecht, 2011; Reps et al., 2012) and pharmacology (Jin et al., 2008; Norén, Bate, Hopstadius, Star, & Edwards, 2008; Wright, Wright, McCoy, & Sittig, 2015).

Despite having the objectives of finding bundles, the *cpsade* algorithm is more complex when it is compared to *apriori*. Therefore, the format of the data is different and requires more manipulation to be able to run the algorithm. Analyzing Table 4.1 suggests that the survey provided insight into when a technology has been adopted. As previously mentioned, there are 3 temporal categories:

(1) Plan to use within two years; (2) Have used for three years or less; (3) Have used for more than three years. Considering the example in Table 4.5, this data needs to be transformed into a format that the *cspade* algorithm can understand. To do so the data needs to be structured into three columns: the sequence ID (SID), the event ID (EID) and the items in the transaction. The preferred format can be found in Table 4.8. The SID represents the firm while the EID represents the time at which a transaction was recorded. For instance, the SID is the unique identifier of a firm, generally starting at 1 and increasing with the number of firms. Since a firm can do multiple transactions (i.e. purchasing technologies at different timeframes), the EID is utilized to provide information on the year of adoption. For example, using a baseline year of 2014, an EID of 1 means that this transaction was done in 2015 (EID = Year of Purchase – 2014). In other words, the higher the EID the later in time a transaction or a purchase is made. The same measures that were presented with the association rules and the *apriori* algorithm are also applicable here: support, confidence and lift.

Table 4.8: Transforming the SAT 2014 data for the *cspade* algorithm

Company	**A**	**B**	**C**	**D**	**E**
Firm 1	0	2	3	1	0
Firm 2	1	1	1	0	0
Firm 3	2	0	0	0	1
Firm 4	3	2	1	1	1
Firm 5	1	1	1	0	0

SID	**EID**	**Items**
1	1	D
1	2	B
1	3	C
2	1	ABC
3	1	E
3	2	A

Practical implications of the *cspade* algorithm

The interpretation of the results remains similar to *apriori*. However, there is a temporality aspect added, which means that the order in which the frequent sequences are viewed is very important. For instance, finding all the rules that have the business intelligence technology B as a consequent can provide information on which technologies are adopted prior to adopting technology B. In this case, this technology represents big data software (e.g., Hadoop). This could help firms find out which technologies should be adopted before big data software, for example. For a provider of these technologies, association rules can give insight into which technologies should be sold in sequence. If a firm wants to purchase a certain technology but does not possess what should have naturally been acquired before, this constitutes a business opportunity to sell two technologies at once in a bundle.

4.5 Summary and conclusion

The general objective of this study is to investigate context the Canadian context of the adoption of emerging technologies and their impact on the propensity to innovate. This can be achieved by using the Survey of Advanced Technologies (SAT 2014). To reach this objective, specific smaller objectives have been presented. A three-part methodology has been elaborated to explain how these technologies impact the propensity the innovate. First, an econometric model examines the joint impact of the number and adopted technologies and OI strategies on innovation. The model uses an Instrumental-Variable Probit Regression (IVPR) to validate five hypotheses regarding the joint impact of adopting technologies and OI strategies. Once this impact understood, the next step consists in examining which technologies are adopted together. This aims to reach objectives (3) and (4) to find and illustrate a network of technology bundles that companies choose to adopt. This is achieved with a Market Basket Analysis (MBA) in order to understand which technologies are firms purchasing. This approach will validate propositions (1), (2) and (3) about the different bundles of technologies that are expected to be adopted. The last step consists in exploring the order in which these technologies have been adopted. This will be done by using an algorithm similar to the one used in the MBA, which aims at finding frequent sequential patterns. This method emphasizes on objectives (5) and (6).

In summary, the econometric model provides an idea on the impact of adoption of technologies and OI strategies. Then, the *apriori* algorithm explores that bundles of technologies that are adopted by companies. Finally, these bundles are analyzed further with the *cspade* algorithm to understand the adoption dynamics within time. With all the results that will stem from these approaches, it will be possible to reach the last objective (7), which aims at providing business and practical recommendations on technology adoption.

CHAPTER 5 REGRESSIONS TO MEASURE THE IMPACT OF TECHNOLOGY ADOPTION ON THE PROPENSITY TO INNOVATE

This chapter first presents the descriptive statistics of the survey sample and then discusses the results of the instrumental-variable probit regressions (IVPR) that estimate the impact of technology adoption on innovation performance. This research differs from previous studies in two aspects: (1) the broad and exhaustive list of technologies available in the survey; and (2) the study of the endogenous effect that technology adoption has on the propensity to innovate.

5.1 Descriptive statistics of the survey sample

Firm size

In Canada, the majority of firms are considered small and medium-sized firms (SMEs). The survey sample is not different in terms of size as shown in Table 5.1 below. More than 80% of companies that responded to the survey had fewer than 100 employees. On the other hand, less than 5% of firms are considered large enterprises with more than 500 employees. Size is used as a control variable in the IVPR analysis. Larger firms tend to have more capital in general, which could play a role in impacting the propensity to innovate.

Table 5.1: Firm size distribution

Firm Size	Frequency	Percentage
10-100	6409	81.00%
100-500	1154	14.59%
500+	349	4.41%
Total	7912	100%

Industry

The industries targeted in the survey can be found in Table 5.2. More than 52% of the firms operate in the manufacturing sector with a two-digit NAICS code from 31 to 33. The other companies are considered service firms and are present in many different sectors. The forestry and logging industry and the utilities sector are amongst the least represented in the survey with 1.38% and 1.68% respectively. The industry is also used as a control variable in the regression analysis, but an adapted Pavitt taxonomy was the preferred method to be included (see Table 5.3). In the regressions, the service industry is omitted so all comparisons are made against it.

Table 5.2: Surveyed industries (SAT 2014)

All surveyed industries	Frequency	Percentage
Utilities (22)	133	1.68%
Manufacturing (31-33)	4117	52.03%
Wholesale trade (41)	1077	13.61%
Professional, scientific and technical services (54)	857	10.83%
Retail trade (44-45)	296	3.74%
Mining, quarrying, and oil and gas extraction (21)	292	3.69%
Transportation and warehousing (48-49)	835	10.55%
Forestry and logging (113)	109	1.38%
Total	7912	100%

Table 5.3: Surveyed industries recoded based on Pavitt (SAT 2014)

All surveyed industries	Frequency	Percentage
Labour-intensive (inlab)	905	11.44%
Resource-intensive (inres)	1346	17.01%
Scale-intensive (inscal)	696	8.80%
Science-intensive (insci)	309	3.91%
Service-intensive (inserv)	4055	51.25%
Specialized suppliers (inspec)	601	7.60%
Total	7912	100%

5.2 Empirical results

The models use an instrumental-variable probit regression (IPVR) for each family of technologies adopted. These models were organized into the different types of innovation either by looking at all the types together, individually or with specific combinations (e.g. technical innovations and non-technical innovation). The models present both stages of the IVPR and will be described in the following sections. The results are presented for the following categories of technologies (in that order): BI, DIC, PF and MHSCL. As a reminder, the DIC and PF family use the same sample of firms because they are both considered as Advanced Manufacturing Technologies (AMTs). The other two families also have a distinct simple. The general hypothesis that is being tested in this analysis is the fact that the adoption of advanced technologies should have a positive impact on the propensity to innovate. The rest of the variables consists of OI practices and product development strategies that may also play a role on innovation propensity. The correlation tables for each regression can be found in Table 5.7 (BI), Table 5.5 (DIC and PF) and Table 5.6 (MHSCL) respectively.

The descriptive statistics of the control variables by type of technology adopted can be found in Table 5.4. The mean and standard deviation values of the age and size seem to be similar. However, the main difference lies in the industry variable. BI technology adopters are mostly concentrated in the service sector (53.8%). On the other hand, 58.8% of AMTs adopters are operating in the manufacturing sector, without surprise. Finally, the sample of MHSCL adopters is more heterogenous with almost an equal share between manufacturing and service firms. The service sector has been omitted in the regressions and represented respectively 53.8%, 41.2% and 49.5% of the samples of BI, DIC and PF, and MHSCL technologies.

Table 5.4: Control variables by type of technology (mean and standard deviation)

Variables	**BI**		**DIC and PF (AMT)**		**MHSCL**	
	mean	SD	mean	SD	mean	SD
ln_size	4.082	1.411	4.155	1.340	4.026	1.344
ln_age	2.431	0.976	2.461	0.952	2.505	0.959
inress	0.145	0.352	0.169	0.374	0.154	0.361
inlab	0.087	0.282	0.118	0.323	0.100	0.300
inscal	0.101	0.301	0.108	0.311	0.100	0.300
inspec	0.078	0.268	0.124	0.330	0.089	0.284
insci	0.051	0.220	0.069	0.253	0.062	0.241

Table 5.5: Correlation Table - BI Technologies Regressions

	allinno	techinno	nontechinno	prodinno	procinno	markinno	orginno	OsloNew	Concurrent Eng.	Cross-funct. Teams	Collab-uni&gvt	Collab-firms	CTI-Benchmarking
allinno	1												
techinno	0.7057	1											
nontechinno	0.6892	0.4094	1										
prodinno	0.4779	0.6772	0.3353	1									
procinno	0.5585	0.7915	0.4113	0.4419	1								
markinno	0.421	0.3068	0.6109	0.3677	0.286	1							
orginno	0.5446	0.3926	0.7902	0.302	0.423	0.3567	1						
OsloNew	0.8825	0.5975	0.7809	0.3643	0.6329	0.4771	0.6171	1					
Concurrent Eng.	0.156	0.1952	0.1453	0.2037	0.1603	0.0959	0.1529	0.1445	1				
Cross-funct. Teams	0.1957	0.2397	0.191	0.2749	0.1801	0.1269	0.2294	0.1702	0.2057	1			
Collab-uni&gvt	0.1577	0.1664	0.1309	0.1408	0.1527	0.0707	0.1469	0.1338	0.1343	0.2165	1		
Collab-firms	0.1475	0.1703	0.1434	0.1847	0.1632	0.1291	0.1851	0.157	0.1429	0.1947	0.1473	1	
CTI-Benchmarking	0.0964	0.138	0.1167	0.1346	0.1562	0.0867	0.1578	0.1116	0.127	0.2353	0.2051	0.1891	1
Sustain. Dev-ESP	0.0807	0.1074	0.0801	0.062	0.1244	0.0379	0.1015	0.0878	0.0834	0.1746	0.222	0.1575	0.2287
PDM & LCM	0.1549	0.1901	0.1777	0.206	0.1687	0.1308	0.2245	0.146	0.2114	0.3182	0.1734	0.1975	0.2145
Outsourcing	0.1919	0.2106	0.1877	0.2324	0.167	0.1671	0.1936	0.1747	0.154	0.2016	0.1239	0.2681	0.1248
ln_size	0.0824	0.1063	0.1078	0.079	0.1275	0.0222	0.1571	0.0779	0.0783	0.237	0.1716	0.0814	0.1075
ln_age	-0.0558	-0.0705	-0.0597	-0.0596	-0.0454	-0.0545	-0.092	-0.0417	-0.0163	-0.0738	-0.0817	-0.0662	-0.0002
inress	-0.0041	0.0109	-0.0057	-0.0612	0.0521	0.0094	-0.0179	0.0132	-0.064	-0.0295	-0.0019	-0.0499	0.0066
inlab	0.067	0.0677	0.0525	0.0512	0.0769	0.0302	0.0648	0.0766	-0.0015	0.0308	-0.0069	-0.0209	0.0266
inscal	0.0026	0.0167	0.0039	0.0403	0.0524	0.0309	0.007	0.0094	-0.0066	0.0424	0.0816	-0.0092	0.0168
inspec	0.0705	0.0574	0.0464	0.0785	0.0515	0.0233	0.0482	0.0651	0.207	0.0957	0.0094	0.0325	0.0024
insci	0.0778	0.0936	0.0243	0.127	-0.0078	0.0384	0.0281	0.0154	0.1496	0.1146	0.0362	0.0068	0.0143
ln_Index_BI	0.1287	0.1711	0.1468	0.1572	0.1362	0.1221	0.1397	0.1103	0.0674	0.123	0.0923	0.1234	0.1097
ln_Index_Measures	0.1259	0.1482	0.1681	0.0948	0.1704	0.1177	0.1949	0.1372	0.0863	0.0876	0.0722	0.1816	0.1404
CAPEX_BI	0.1582	0.1491	0.1465	0.1146	0.1828	0.1274	0.1461	0.1635	0.0178	0.0424	0.013	0.0778	0.0572
Empl Recruit	0.1937	0.2059	0.2328	0.1901	0.2097	0.1955	0.2324	0.201	0.1545	0.2256	0.0988	0.1711	0.1555

	Sustain. Dev-ESP	PDM & LCM	Outsourcing	ln_size	ln_age	inress	inlab	inscal	inspec	insci	ln_Index_BI	ln_Index_Measures	CAPEX_BI	Empl Recruit
Sustain. Dev-ESP	1													
PDM & LCM	0.2529	1												
Outsourcing	0.1293	0.2488	1											
ln_size	0.2111	0.249	0.1542	1										
ln_age	-0.0501	-0.0728	-0.0828	-0.0644	1									
inress	0.0702	-0.0174	-0.1146	0.0275	-0.0328	1								
inlab	-0.0032	-0.0491	-0.0019	-0.0473	0.0506	-0.1272	1							
inscal	0.0291	0.012	-0.0474	0.0233	-0.0377	-0.1381	-0.1035	1						
inspec	-0.0615	0.0206	0.0873	-0.0506	0.0054	-0.1199	-0.0898	-0.0975	1					
insci	-0.0423	0.0648	0.115	-0.0256	0.0049	-0.0957	-0.0717	-0.0778	-0.0675	1				
ln_Index_BI	0.1289	0.1485	0.1364	0.1271	-0.0758	-0.0605	-0.0505	0.0026	-0.0622	0.0172	1			
ln_Index_Measures	0.1028	0.1467	0.1249	0.0259	-0.0347	0.0136	0.0153	-0.0308	0.0093	0.0162	0.1668	1		
CAPEX_BI	0.0516	0.0568	0.0897	0.0474	-0.0335	-0.0135	-0.0302	-0.0237	-0.0209	-0.0329	0.2188	0.1434	1	
Empl Recruit	0.1016	0.1829	0.1824	0.1586	-0.0009	-0.0583	0.0752	-0.0204	0.0429	0.0416	0.1778	0.2394	0.1852	1

Table 5.6: Correlation Table – DIC and PF Technologies Regressions

	allinno	techinno	nontechinno	prodinno	procinno	markinno	orginno	OsloNew	Concurrent Eng.	Cross-funct. Teams	Collab-uni&gvt	Collab-firms	CTI-Benchmarking
allinno	1												
techinno	0.7266	1											
nontechinno	0.6043	0.3719	1										
prodinno	0.4498	0.619	0.2753	1									
procinno	0.5436	0.7481	0.4067	0.3626	1								
markinno	0.3438	0.2738	0.5689	0.3218	0.2716	1							
orginno	0.4871	0.363	0.806	0.2492	0.4187	0.3397	1						
OsloNew	0.8255	0.5751	0.7321	0.3039	0.6585	0.4165	0.5901	1					
Concurrent Eng.	0.1543	0.1924	0.1418	0.1957	0.1517	0.0864	0.1613	0.1315	1				
Cross-funct. Teams	0.1300	0.1653	0.1194	0.2351	0.0994	0.0766	0.1484	0.0944	0.1502	1			
Collab-uni&gvt	0.1072	0.1018	0.0844	0.0729	0.093	0.0438	0.1041	0.0895	0.1352	0.1727	1		
Collab-firms	0.1058	0.1398	0.101	0.1466	0.1233	0.091	0.1502	0.097	0.1588	0.2007	0.1558	1	
CTI-Benchmarking	0.0764	0.111	0.098	0.1307	0.1112	0.1065	0.125	0.0839	0.121	0.1835	0.1725	0.2005	1
Sustain. Dev-ESP	0.0704	0.0888	0.0306	0.0318	0.096	0.0648	0.0582	0.058	0.0861	0.1223	0.2098	0.1812	0.2465
PDM & LCM	0.1263	0.1482	0.1426	0.1576	0.1283	0.1421	0.1768	0.116	0.2029	0.2603	0.1389	0.1852	0.1925
Outsourcing	0.1226	0.1668	0.1272	0.1735	0.1074	0.1168	0.1722	0.1102	0.1858	0.1649	0.0941	0.2394	0.1181
ln_size	0.0514	0.0539	0.0725	0.036	0.0758	0.0181	0.1105	0.0565	0.0717	0.2124	0.144	0.0824	0.1061
ln_age	-0.0289	-0.0534	-0.0201	-0.0442	-0.0217	-0.0339	-0.0647	-0.0152	-0.0293	-0.1069	-0.0556	-0.0925	-0.0205
inress	-0.0227	-0.0312	-0.028	-0.1014	0.0137	-0.0027	-0.0611	-0.0062	-0.1233	-0.061	0.0019	-0.1192	-0.0167
inlab	0.0474	0.0502	0.0596	0.0209	0.0547	0.0535	0.0455	0.064	-0.0495	0.0033	-0.0365	-0.039	0.0085
inscal	-0.0148	-0.0047	0.0012	0.0126	0.0271	0.0523	0.0109	-0.0057	-0.0333	0.0165	0.012	-0.0307	-0.0077
inspec	0.0449	0.0285	0.027	0.0872	0.0156	0.0087	0.01	0.0322	0.1871	0.0728	0.0276	0.0471	-0.0225
insci	0.0616	0.0789	0.0022	0.1174	-0.0304	0.0088	0.0275	-0.0049	0.1263	0.0788	0.0646	0.0281	0.0377
ln_Index_DIC	0.1776	0.2210	0.1529	0.1559	0.1939	0.0726	0.1892	0.1658	0.2173	0.2628	0.1588	0.186	0.1721
ln_Index_PF	0.154	0.1759	0.1234	0.1584	0.1609	0.0546	0.1287	0.1308	0.2128	0.2127	0.154	0.1167	0.1315
ln_Index_Measures	0.1074	0.1257	0.1300	0.1274	0.1324	0.0648	0.1608	0.1098	0.0903	0.1245	0.1263	0.1569	0.0958
CAPEX_DIC	0.1295	0.1025	0.1281	0.0574	0.1297	0.0872	0.1403	0.1343	0.088	0.0658	0.0191	0.0642	0.0891
Empl Recruit	0.1379	0.1361	0.1665	0.1312	0.1349	0.1477	0.1573	0.1365	0.1401	0.1544	0.0683	0.1552	0.1214

	Sustain. Dev-ESP	PDM & LCM	Outsourcing	ln_size	ln_age	inress	inlab	inscal	inspec	insci	ln_Index_DIC	ln_Index_PF	ln_Index_Measures	CAPEX	Empl Recruit
Sustain. Dev-ESP	1														
PDM & LCM	0.2074	1													
Outsourcing	0.1162	0.1945	1												
ln_size	0.1957	0.2588	0.1362	1											
ln_age	-0.0225	-0.0999	-0.0779	-0.0384	1										
inress	0.0456	-0.048	-0.186	0.0009	-0.0071	1									
inlab	-0.0342	-0.0608	-0.0125	-0.0701	0.071	-0.1649	1								
inscal	0.0359	-0.0245	-0.0129	-0.0032	-0.0354	-0.157	-0.1277	1							
inspec	-0.0751	-0.0345	0.1139	-0.0544	-0.0057	-0.1694	-0.1378	-0.1311	1						
insci	-0.0624	0.0732	0.1128	-0.0319	0.0204	-0.1223	-0.0995	-0.0947	-0.1022	1					
ln_Index_DIC	0.1945	0.2488	0.1685	0.3239	-0.0532	-0.0502	0.0008	0.0251	0.0676	0.0705	1				
ln_Index_PF	0.0663	0.15	0.1605	0.185	-0.0252	-0.0347	0.1468	0.0093	0.1552	0.0675	N/A[12]	1			
ln_Index_Measures	0.0797	0.1268	0.1584	0.0376	-0.0306	-0.0097	0.0085	-0.0575	0.0745	0.0101	0.1871	0.1382	1		
CAPEX_DIC	0.0887	0.0674	0.0775	0.1245	0.0208	-0.0453	0.0315	-0.0167	0.0252	-0.0357	0.1568	0.0991	0.1099	1	
Empl Recruit	0.0762	0.1022	0.1634	0.1141	-0.0177	-0.0919	0.051	-0.061	0.0551	0.0131	0.2031	0.2007	0.2144	0.1725	1

[12] DIC and PF use the sample of firms and the same variables, with the exception of the variable representing the number of adopted technologies. Because the regressions are run separately on each family of technology, there is no correlation for ln_Index_DIC and ln_Index_PF because they are not run in the same regression.

Table 5.7: Correlation Table – MHSCL Technologies Regressions

	allinno	techinno	nontechinno	prodinno	procinno	markinno	orginno	OsloNew	Concurrent Eng.	Cross-funct. Teams	Collab-uni&gvt	Collab-firms	CTI-Benchmarking
allinno	1												
techinno	0.7481	1											
nontechinno	0.72	0.4664	1										
prodinno	0.5292	0.7074	0.3645	1									
procinno	0.5935	0.7933	0.4654	0.4667	1								
markinno	0.4561	0.3336	0.6335	0.3511	0.3166	1							
orginno	0.5662	0.4351	0.7864	0.3271	0.4691	0.3596	1						
OsloNew	0.8874	0.638	0.8113	0.4098	0.6688	0.514	0.638	1					
Concurrent Eng.	0.1657	0.2124	0.147	0.2156	0.1796	0.0876	0.1707	0.1558	1				
Cross-funct. Teams	0.2105	0.2392	0.2014	0.2693	0.1958	0.1299	0.2189	0.211	0.2054	1			
Collab-uni&gvt	0.1626	0.1848	0.14	0.1607	0.1705	0.0839	0.1472	0.1486	0.1684	0.229	1		
Collab-firms	0.1803	0.2072	0.1767	0.2063	0.2055	0.1458	0.213	0.1797	0.1626	0.2346	0.1911	1	
CTI-Benchmarking	0.125	0.1536	0.1348	0.1552	0.1627	0.1095	0.1612	0.1372	0.1628	0.2252	0.1951	0.1959	1
Sustain. Dev-ESP	0.1012	0.1126	0.1116	0.0784	0.1254	0.0869	0.129	0.108	0.0965	0.1774	0.1948	0.1645	0.2408
PDM & LCM	0.1546	0.1881	0.1687	0.2067	0.1655	0.1233	0.219	0.1542	0.201	0.2972	0.1771	0.2093	0.2008
Outsourcing	0.2042	0.2449	0.1915	0.2351	0.2054	0.1551	0.2107	0.1927	0.1895	0.2174	0.1577	0.2708	0.122
ln_size	0.0911	0.1083	0.0849	0.0795	0.1135	0.0097	0.123	0.0862	0.11	0.2548	0.1847	0.1072	0.1251
ln_age	-0.0514	-0.0642	-0.0655	-0.0723	-0.0427	-0.055	-0.0939	-0.0442	-0.0692	-0.126	-0.0816	-0.0712	-0.0069
inress	0.0164	0.0086	0.0258	-0.0239	0.022	0.0302	0.0014	0.0213	-0.0611	-0.0425	0.0007	-0.0593	-0.0129
inlab	0.0642	0.0507	0.0432	0.0375	0.0602	0.042	0.0353	0.0672	-0.0073	0.0223	-0.02	-0.0398	-0.0084
inscal	-0.0115	0.0137	-0.0297	0.0234	0.0402	0.0029	-0.0243	-0.01	-0.0037	0.0671	0.0501	0.0182	0.0539
inspec	0.0756	0.0772	0.0291	0.1017	0.0469	-0.0146	0.0488	0.0497	0.1948	0.1042	0.0399	0.058	-0.0066
insci	0.0859	0.1052	0.0519	0.1288	0.0414	0.048	0.0422	0.062	0.1463	0.1402	0.075	0.0684	0.0558
ln_Index_MHSCL	0.1243	0.1463	0.131	0.1047	0.1502	0.0793	0.166	0.1223	0.0592	0.1744	0.0978	0.1434	0.1339
ln_Index_Measures	0.154	0.1653	0.19	0.1324	0.1901	0.1461	0.2058	0.1717	0.0928	0.1052	0.1146	0.1526	0.1269
CAPEX_MHSCL	0.1724	0.1762	0.1988	0.0892	0.2174	0.1399	0.236	0.2	0.0196	0.0911	0.0585	0.1004	0.0962
Empl Recruit	0.2077	0.2118	0.2196	0.1907	0.2218	0.1701	0.2299	0.2131	0.1515	0.1879	0.1173	0.1915	0.1503

	Sustain. Dev-ESP	PDM & LCM	Outsourcing	ln_size	ln_age	inress	inlab	inscal	inspec	insci	ln_Index_MHSCL	ln_Index_Measures	CAPEX_MHSCL	Empl Recruit
Sustain. Dev-ESP	1													
PDM & LCM	0.2296	1												
Outsourcing	0.127	0.2483	1											
ln_size	0.2238	0.2418	0.1444	1										
ln_age	-0.0345	-0.0646	-0.0435	-0.059	1									
inress	0.062	-0.0241	-0.1156	0.0141	-0.0206	1								
inlab	-0.0061	-0.0563	-0.0319	-0.0493	0.0613	-0.1423	1							
inscal	0.0391	-0.0052	-0.0044	0.0394	-0.0473	-0.1423	-0.1112	1						
inspec	-0.0631	0.036	0.1082	-0.0052	-0.0077	-0.1332	-0.104	-0.104	1					
insci	-0.0407	0.0887	0.1576	-0.0271	0.006	-0.1097	-0.0857	-0.0857	-0.0802	1				
ln_Index_MHSCL	0.1904	0.2401	0.1185	0.3752	-0.0753	-0.018	-0.0174	0.0192	-0.0179	0.0354	1			
ln_Index_Measures	0.1039	0.1491	0.1225	0.074	-0.0367	0.0414	-0.0107	-0.0295	0.0132	-0.0107	0.1597	1		
CAPEX_MHSCL	0.0821	0.0754	0.083	0.1023	-0.0188	0.0026	-0.0189	0.0143	-0.0432	-0.0241	0.1915	0.212	1	
Empl Recruit	0.1192	0.1714	0.21	0.1524	-0.0229	-0.0496	0.0259	-0.0229	0.0945	0.0205	0.1168	0.2131	0.1688	1

5.2.1 Results of the BI technologies regressions

The results of the IVPR on BI technologies are presented in Table 5.8. The descriptive statistics are presented in Table 8.1 in Appendix A. Correcting for endogeneity, collaboration with universities and governments had a positive effect that was significant when at least one type of innovation was reported (Model A). While the impact was less significant, it was similarly the case for technical innovation, but not for product or process innovation individually. This is in line with results from previous studies that found that universities are knowledge sources associated with low risks (Brettel & Cleven, 2011), which can improve firms' innovation performance considerably (Miotti & Sachwald, 2003). This kind of collaboration is seen as less costly than collaboration with other companies (Tether, 2002), which is why it might be more accessible regardless of the type of innovation being developed. More recently, Najafi-Tavani, Najafi-Tavani, Naudé, Oghazi, and Zeynaloo (2018) observed that universities and research organizations can increase innovation propensity for both product and process innovations. Only 20% of businesses said that they cooperated with universities and governments. This could explain why there was a significant effect when analyzing the combined impact of all types of innovation and of technical innovation. The individual effect did not have a significant coefficient because of the low adoption rate this OI practice.

On the other hand, collaboration with other firms seemed to only affect product innovation (the sole positive and significant coefficient). Traditionally, OI practices were generally focussed on product innovation so it is not surprising to see this type of collaboration having an influence on new product development. Companies nurturing strong cooperation relationships with external partners are more likely to have a higher propensity to innovate (De Faria, Lima, & Santos, 2010; Mention, 2011). For instance, working with suppliers (Hallikas, Virolainen, & Tuominen, 2002) or with competitors (J. Wu, 2014) can have a positive impact on product innovation propensity. This can be explained by the fact that inter-firm knowledge exchange becomes more prominent with collaboration (Luzzini, Amann, Caniato, Essig, & Ronchi, 2015). However, to be able to fully profit from these available information sources, a firm should have a high level of absorptive capacity (AC) (Erickson & Rothberg, 2009), which can facilitate the reconfiguration and integration of new acquired knowledge (Y.-S. Chen, Lin, & Chang, 2009; Winkelbach & Walter, 2015). In the specific case of enterprises adopting BI technologies, they require an elevated degree of AC (Elbashir, Collier, & Sutton, 2011), which is considered to be a main determinant of a firm's competitive advantage (Tzokas, Kim, Akbar, & Al-Dajani, 2015). Combined with collaboration, AC can help firms benefit from a higher propensity to develop new products (Najafi-Tavani et al., 2018). As a reference to the previous literature, it can be argued that the adoption of OI practices and advanced BI technologies can have a positive impact on the propensity to innovate.

Other methods such as concurrent engineering (CE) and cross-functional design teams (CFT) also had a significant and positive effect on product innovation. This was expected as both practices are meant to increase creativity in new product development. For instance, CE focusses on multifunctional groups, which has many advantages: amplified creativity and better decision-making (Donnellon, 1993), and improved communication and organizational learning (Henke, Krachenberg, & Lyons, 1993; McKee, 1992). This can lead to shorter development times, an increased propensity to innovate, and an ameliorated quality (Fleischer & Liker, 1992; Koufteros, Vonderembse, & Doll, 2001). Because of their multidisciplinary aspect, teams emphasizing on CE tend to know about other technical fields including their own (Tummala, Chin, & Ho, 1997). The same effect is seen with process innovation, which can be explained in a similar fashion. Teams working concurrently in an integrated workflow to design a new product may be more prominent in incorporating process improvements that reduce the cost and better the quality of a product. For example, Blackburn, Hoedemaker, and Van Wassenhove (1996) stated that the overlap of activities must be managed by a clear strategy, which can involve how to prioritize the scheduling of parallel functions (Nicoletti & Nicolo, 1998). It can be then argued that process innovation can also become the result of the adoption of CE because it forces the introduction of new approaches.

This being said, the success of any CE initiative is dependent on the implementation of cross-functional teams (CFTs) (Koufteros et al., 2001), which is another factor that contributes to the propensity to innovate. When separated into technical and non-technical innovation, the effect of CFTs is significant for technical innovations ($p<0.01$), which is probably driven by product innovation as well ($p<0.001$). According to Lopes Pimenta, Lago da Silva, and Tate (2014), cross-functional teams contributed to facilitate the integration between internal departments through formal and informal collaboration. As external cooperation can play a role on the propensity to innovate, it can be argued that CFTs will have the same effect. Coordination between a firm's different internal units can lead to creativity, which will result in faster times to develop a new product (Bunduchi, 2009). As a consequence, teams that can enhance their product innovation propensity have a degree of learning, assimilation and coordination (Darawong, 2018). In other words, it means that CFTs rely on their absorptive capacity to integrate knowledge from different business units. Furthermore, adopting BI technologies increased the propensity to innovate, which can also be explained by AC. Not only is it required to adopt these technologies, but it is crucial to understand the insights that are generated from BI instruments. Using various types of knowledge obtained from BI can lead managers to make better decisions with regards to business activities (Sharda, Delen, Turban, Aronson, & Liang, 2014; Williams & Williams, 2004)

In terms of control variables, neither age nor size did have a significant effect on the propensity to innovate. Size is only significant in the case of marketing innovation and the effect is negative. In other words, only smaller firms tend to introduce marketing innovations. Some of the sectors' coefficients are positive and significant: inress inlab, inspec and insci. In fact, most of the industries show a beneficial impact on the propensity to innovate when compared to the services sector. However, there are a few standout results that should be noted. First, resource-based (inress) was the only industry that does not have a significant effect in the case of product innovation. This sector is comprised of food, beverage and wood manufacturing. Second, science-based industries (insci) do not have a significant effect on process, organizational and marketing innovation. The same result was observed when combining all three types of non-technological innovation (i.e. process, marketing, and organizational in Model H) and when regrouping product and process innovations (Model C). This sector of high-tech manufacturing firms is more prominent in product innovations because they're highly R&D intensive and collaborate with universities (Ada Leiponen, 2000; Mansury & Love, 2008). Similar patterns are observed with the other industries with the addition that there is a significant effect for all types of innovation when contrasted to the service sector. In particular, the scale-intensive sector (inscal) has a significant effect on product, process and marketing innovations. Specifically, the impact on marketing innovation may be explained by the heterogeneity of the sample used. The split between manufacturing and service firms is almost equal, with service businesses being slightly more dominant (53.77% adoption by service companies compared to 46.33% for manufacturing firms). While it is less significant for scale-intensive and specialized suppliers, it has a positive effect on resource-intensive and labour-intensive sector. These companies have all adopted BI technologies, which are known to enable powerful data analysis that can result in a competitive advantage to enterprises able to profit from it (M. E. Porter & Heppelmann, 2015). Marketing innovation is more prominent in businesses that are less R&D intensive (Hall & Bagchi-Sen, 2007), which further confirms the heterogeneity of the sample. Moreover, science-intensive firms have a significant effect for product innovation, yet not for marketing innovation. These outcomes highlight what was previously found in the literature concerning the similar innovation patterns between manufacturing and service enterprises (Arvanitis, 2008; James H Love & Mansury, 2007). Some services have more resemblances with manufacturing firms than with other services (Preissl, 2000), but from these results, it can be argued that some manufacturing businesses may behave more like service firms. This is due to the fact that it is not only product innovation that is significant and positive, but also marketing innovation. This can further be due to the sample of companies that have adopted BI technologies, which are mostly used for the data insights they may provide.

Table 5.8: Results from IVPR of BI technologies (N=1564) [13]

MODELS	A	B	C	D	E	F	G	H
	allinno	techinno	nontechinno	prodinno	procinno	markinno	orginno	businno
Second Stage Probit Regression – Dependent variable = Type of innovation (models A to H)								
ln_Index_BI	2.517**** (0.172)	2.358**** (0.2)	2.460**** (0.164)	1.661**** (0.308)	2.384**** (0.157)	2.089**** (0.216)	2.297**** (0.179)	2.435**** (0.165)
Collab-uni&gvt	0.348*** (0.127)	0.215** (0.101)	0.098 (0.088)	0.121 (0.09)	0.113 (0.084)	0 (0.08)	0.084 (0.084)	0.138 (0.097)
Collab-firms	0.072 (0.085)	0.081 (0.079)	0.021 (0.072)	0.158** (0.077)	0.068 (0.07)	0.064 (0.07)	0.097 (0.072)	0.095 (0.079)
Concurrent Eng.	0.316** (0.141)	0.383*** (0.12)	0.152 (0.096)	0.324*** (0.102)	0.184** (0.091)	0.054 (0.085)	0.116 (0.091)	0.207* (0.11)
Cross-funct. Teams	0.249** (0.112)	0.293*** (0.099)	0.13 (0.085)	0.414**** (0.092)	0.044 (0.078)	0.049 (0.077)	0.159* (0.083)	0.11 (0.091)
Outsourcing	0.241** (0.103)	0.209** (0.089)	0.13 (0.081)	0.271*** (0.085)	0.074 (0.075)	0.158** (0.077)	0.075 (0.076)	0.150* (0.088)
CTI-Benchmarking	-0.069 (0.12)	0.053 (0.112)	0.017 (0.1)	0.069 (0.103)	0.104 (0.098)	-0.012 (0.091)	0.105 (0.099)	0.027 (0.111)
Sustain. Dev-ESP	-0.197 (0.139)	-0.112 (0.129)	-0.203* (0.114)	-0.259** (0.118)	-0.065 (0.112)	-0.229** (0.105)	-0.186* (0.112)	-0.122 (0.128)
PDM & LCM	0.275* (0.155)	0.216* (0.123)	0.159 (0.109)	0.241** (0.109)	0.04 (0.096)	0.081 (0.094)	0.247** (0.107)	0.092 (0.116)

[13] The average VIF is 1.15, ranging between 1.03 and 1.29, which highlights that there is no collinearity.

Table 5.8: Results from IVPR of BI technologies (N=1564… con'td)

ln_size[14]	-0.028 (0.027)	-0.021 (0.026)	-0.012 (0.024)	-0.034 (0.025)	0.004 (0.024)	-0.057** (0.023)	0.022 (0.025)	-0.029 (0.025)
ln_age	0.025 (0.036)	0.009 (0.035)	0.022 (0.032)	0.001 (0.034)	0.037 (0.031)	0.005 (0.032)	-0.014 (0.032)	0.033 (0.033)
inress	0.303*** (0.099)	0.364**** (0.096)	0.269*** (0.091)	0.135 (0.098)	0.452**** (0.09)	0.312**** (0.089)	0.222** (0.09)	0.340**** (0.095)
inlab	0.599**** (0.146)	0.562**** (0.128)	0.433**** (0.118)	0.437**** (0.12)	0.558**** (0.115)	0.337*** (0.11)	0.477**** (0.115)	0.586**** (0.135)
inscal	0.136 (0.118)	0.194* (0.113)	0.113 (0.105)	0.289** (0.113)	0.321*** (0.105)	0.239** (0.103)	0.11 (0.104)	0.172 (0.111)
inspec	0.565**** (0.16)	0.413*** (0.138)	0.353*** (0.125)	0.403*** (0.136)	0.459**** (0.12)	0.285** (0.12)	0.369*** (0.122)	0.489**** (0.139)
insci	0.523** (0.238)	0.525*** (0.194)	0.047 (0.15)	0.653**** (0.179)	0.001 (0.141)	0.154 (0.142)	0.081 (0.146)	0.025 (0.156)
constant	-2.208**** (0.255)	-2.305**** (0.252)	-2.378**** (0.219)	-1.911**** (0.329)	-2.645**** (0.191)	-2.173**** (0.249)	-2.482**** (0.212)	-2.185**** (0.238)
First Stage OLS Regression – Dependent variable = ln_Index_BI								
Concurrent Eng.	0.016 (0.024)	0.016 (0.024)	0.014 (0.024)	0.016 (0.024)	0.016 (0.024)	0.015 (0.024)	0.015 (0.024)	0.015 (0.024)
Cross-funct. Teams	0.026 (0.021)	0.027 (0.021)	0.025 (0.021)	0.027 (0.021)	0.027 (0.021)	0.025 (0.021)	0.026 (0.021)	0.026 (0.021)
Collab-uni&gvt	0.02 (0.023)	0.02 (0.023)	0.02 (0.023)	0.02 (0.023)	0.02 (0.023)	0.02 (0.023)	0.02 (0.023)	0.02 (0.023)
Collab-firms	0.018 (0.019)	0.018 (0.019)	0.017 (0.019)	0.019 (0.019)	0.018 (0.019)	0.018 (0.019)	0.017 (0.019)	0.018 (0.019)
CTI-Benchmarking	0.026 (0.025)	0.026 (0.025)	0.025 (0.025)	0.027 (0.025)	0.026 (0.025)	0.026 (0.025)	0.025 (0.025)	0.026 (0.025)
Sustain. Dev-ESP	0.059** (0.03)	0.059** (0.03)	0.059** (0.03)	0.059** (0.03)	0.059** (0.03)	0.060** (0.03)	0.059** (0.03)	0.059** (0.03)
PDM & LCM	0.037 (0.025)	0.037 (0.025)	0.036 (0.025)	0.038 (0.025)	0.037 (0.025)	0.037 (0.025)	0.036 (0.025)	0.037 (0.025)
Outsourcing	0.033* (0.02)	0.033* (0.02)	0.033* (0.02)	0.033* (0.02)	0.033* (0.02)	0.033* (0.02)	0.033* (0.02)	0.033* (0.02)
ln_size	0.012* (0.006)	0.012* (0.006)	0.012* (0.006)	0.012* (0.006)	0.012* (0.006)	0.012* (0.006)	0.012* (0.006)	0.012* (0.006)
ln_age	-0.018** (0.009)	-0.018** (0.009)	-0.018** (0.009)	-0.018** (0.009)	-0.017** (0.009)	-0.018** (0.009)	-0.018** (0.009)	-0.018** (0.009)
inress	-0.076*** (0.025)	-0.077*** (0.025)	-0.077*** (0.025)	-0.076*** (0.025)	-0.077*** (0.025)	-0.076*** (0.025)	-0.077*** (0.025)	-0.076*** (0.025)
inlab	-0.088*** (0.031)	-0.087*** (0.031)	-0.091*** (0.031)	-0.086*** (0.031)	-0.087*** (0.031)	-0.089*** (0.031)	-0.089*** (0.031)	-0.089*** (0.031)
inscal	-0.027 (0.029)	-0.027 (0.029)	-0.027 (0.029)	-0.027 (0.029)	-0.027 (0.029)	-0.027 (0.029)	-0.027 (0.029)	-0.027 (0.029)
inspec	-0.118**** (0.034)	-0.118**** (0.034)	-0.119**** (0.034)	-0.117**** (0.034)	-0.118**** (0.034)	-0.119**** (0.034)	-0.119**** (0.034)	-0.118**** (0.034)
insci	-0.024 (0.04)	-0.024 (0.04)	-0.026 (0.04)	-0.023 (0.04)	-0.023 (0.04)	-0.025 (0.04)	-0.025 (0.04)	-0.024 (0.04)
ln_Index_Measures	0.076**** (0.02)	0.085**** (0.02)	0.088**** (0.019)	0.073*** (0.023)	0.087**** (0.019)	0.075**** (0.02)	0.099**** (0.019)	0.078**** (0.02)
CAPEX_BI[a]	0.029**** (0.004)	0.029**** (0.004)	0.025**** (0.004)	0.031**** (0.004)	0.030**** (0.004)	0.028**** (0.004)	0.026**** (0.004)	0.028**** (0.004)
Empl Recruit	0.080**** (0.017)	0.072**** (0.018)	0.089**** (0.016)	0.071**** (0.019)	0.070**** (0.016)	0.086**** (0.017)	0.078**** (0.016)	0.082**** (0.017)
constant	0.885**** (0.042)	0.877**** (0.042)	0.882**** (0.042)	0.885**** (0.043)	0.875**** (0.041)	0.889**** (0.042)	0.870**** (0.042)	0.885**** (0.042)

[14] The square of size has been tested and has not yielded significant results.

Table 5.8: Results from IVPR of BI technologies (N=1564… con'td and end)

N	1564	1564	1564	1564	1564	1564	1564	1564
ll	-1008.705	-1220.735	-1280.247	-1414.99	-1376.152	-1515.217	-1377.317	-1118.194
chi2	638.255****	603.823****	621.055****	359.988****	668.484****	270.33****	624.762****	601.388****
chi2_exog	45.751****	35.922****	51.354****	12.509****	60.436****	33.993****	49.077****	53.343****
overid	0.193	0.565	0.015	0.185	0.787	0.051[b]	0.069	0.184
* p<0.1, ** p<0.05, *** p<0.01, **** p<0.001								

a: The CAPEX variable used in this regression is a percentage of total expenditures on advanced technologies. The total amount of CAPEX has been tested and no major changes in coefficients and significance have been observed, besides those enumerated below.

b: The coefficient becomes 0.018, suggesting the model is over specified.

5.2.2 Results of the DIC technologies regressions

The descriptive statistics of the DIC and PF technologies sample are presented in Table 8.2 in Appendix A. These technologies cover the advanced manufacturing technologies and use the identical sample of firms. This means that all the variables are the same, with the exception of the variable containing the number of techs adopted in each category. The results from the IVPR of DIC technologies are shown in Table 5.9.

For this sample of firms, collaboration and OI practices do not seem to have a significant impact on innovation. Concurrent engineering has no effect in this sample of companies. In terms of cross-functional teams (CFT), there are some mixed results. Taking into account the possible estimation bias due to the endogeneity of the regressors, the coefficient regarding product innovation is positive and significant ($p<0.05$), which was expected according to the literature. CFT can increase the propensity to develop new products amongst the firms adopting DIC technologies. Novel products need be designed by involving many different actors. Creativity is an integral part of CFT and this can lead to heightened innovativeness in new product creation (Bunduchi, 2009). Furthermore, the use of CFTs facilitates the efficient exploitation of resources which results in a higher capacity to design quality products and services and increase creativity and innovation (Pinto, Pinto, & Prescott, 1993). These are in line with those found in the BI technologies sample discussed above. However, CFTs appears to have a negative and significative effect for process innovation and for model H which comprises the recent Oslo Manual definition of business process innovations (i.e. process, marketing or organizational). The literature about CFT has focussed mainly on the development of new products (Lopes Pimenta et al., 2014). Nevertheless, rigid tactics may involve several change management initiatives because one variation in the system will affect everything else (Hannan & Freeman, 1984; Tushman & Romanelli, 1985). In other words, the deployment of CFTs may require a transformation in the organizational strategy, which can play a role in shaping organizational structure (Wolf & Egelhoff, 2001). If companies go through a lot of change management between the adoption of new technologies and the implementation of CFTs, it could be argued that it will negatively impact non-technological innovations. While the organizational strategy is to focus on product innovation, it can be difficult to develop new processes. Amongst the barriers to innovation identified in the literature, a lack of information on technology and a shortage of qualified personnel may be the cause in this case (Hölzl & Janger, 2014). Cross-functional design teams require interaction and collaboration between the internal functions of an organization (Kahn & Mentzer, 1996), which includes process improvements, marketing and corporate strategy departments. Because companies are focussed on implementing CFTs efficiently and recruiting new staff to adopt advanced DIC technologies, process innovation may come second because there will be fewer resources directed towards this type of innovation. Furthermore, the sample of firms that adopted these technologies is concentrated in the manufacturing sector, which is traditionally focussed on product innovation. It is logical to believe that initiatives aimed at increasing the tendency to develop new products may hinder the ability to work on process improvements.

In terms of control variables, size had a negative and significant effect in all the models. Smaller companies adopting DIC technologies tend to be more innovative than their counterparts. This result is not in accordance with previous literature. For instance, Hipp, Tether, and Miles (2000) determined that firm size increases the tendency to innovate but decreases innovation performance. Adopting these advanced manufacturing technologies could be a major driver for smaller firms in terms of propensity to innovate, while larger corporations may focus more on collaboration and OI practices. Due to the flexibility of smaller businesses, it might be easier for them to adopt new technologies, provided they have enough capital. It should be noted that small firms are being pressured to adopt AMTs because of soaring external competition and increasing demand from customers (Ordoobadi & Mulvaney, 2001). A large portion of the survey sample (81%) is composed of small firms with fewer than 100 employees, which could explain why smaller firms tend to be more innovative in this case.

Mixed findings are observed in terms of industry impact. Specialized suppliers (inspec) tended to have a negative and significant effect on organizational ($p<0.01$) innovations. This means that firms in this industry have a lower propensity to innovate when it comes to organizational innovations. For the science-intensive sector (insci), similar results were obtained. In general, it has a negative impact on innovation, especially for non-technical ($p<0.01$), process ($p<0.01$), organizational ($p<0.05$), and business process ($p<0.01$) innovations. However, in the case of product innovation, a positive effect but less significant was observed ($p<0.1$). Compared to the sample of companies that adopted BI technologies, this one is completely different. There are a lot more manufacturing firms contrasted to service firms that have adopted DIC technologies, which was anticipated. The results are in accordance with the literature where it was found that non-technological innovations, such as marketing and organizational, are more prominent in the services industry in the form of management or cooperation practices (Tether, 2005). In other words, it was anticipated that the high-tech manufacturing sector might have a lower propensity to innovate when it comes to non-technological innovations, compared to the service sector.

Table 5.9: Results from IVPR of DIC technologies (N=1412)

MODELS	A	B	C	D	E	F	G	H
	allinno	techinno	nontechinno	prodinno	procinno	markinno	orginno	businno
Second Stage Probit Regression – Dependent variable = Type of innovation (models A to H)								
ln_Index_DIC	1.956**** (0.127)	1.689**** (0.229)	1.779**** (0.141)	1.168**** (0.299)	1.739**** (0.169)	1.367**** (0.233)	1.728**** (0.154)	1.873**** (0.142)
Collab-uni&gvt	0.104 (0.111)	0.023 (0.104)	0.018 (0.085)	-0.057 (0.088)	0.016 (0.086)	-0.063 (0.08)	0.031 (0.084)	0.05 (0.096)
Collab-firms	-0.048 (0.088)	0.019 (0.095)	-0.068 (0.075)	0.042 (0.085)	-0.002 (0.08)	-0.029 (0.076)	-0.003 (0.077)	-0.055 (0.083)
Concurrent Eng.	0.133 (0.152)	0.308* (0.159)	-0.022 (0.099)	0.179 (0.117)	0.053 (0.106)	-0.097 (0.09)	-0.016 (0.097)	-0.001 (0.114)
Cross-funct. Teams	-0.09 (0.099)	0.04 (0.111)	-0.128 (0.081)	0.277** (0.113)	-0.166** (0.08)	-0.153* (0.079)	-0.111 (0.081)	-0.170** (0.086)
Outsourcing	0.092 (0.092)	0.217** (0.1)	0.089 (0.077)	0.165** (0.083)	0.059 (0.077)	0.116 (0.076)	0.139* (0.078)	0.087 (0.085)
CTI-Benchmarking	-0.07 (0.119)	0.072 (0.13)	0.022 (0.102)	0.171 (0.113)	0.033 (0.103)	0.07 (0.098)	0.053 (0.101)	-0.013 (0.111)
Sustain. Dev-ESP	-0.174 (0.157)	-0.069 (0.166)	-0.390**** (0.118)	-0.289** (0.129)	-0.124 (0.132)	-0.151 (0.119)	-0.341*** (0.118)	-0.253* (0.136)
PDM & LCM	0.135 (0.16)	0.145 (0.147)	0.043 (0.11)	0.117 (0.118)	-0.011 (0.107)	0.126 (0.109)	0.063 (0.109)	0.013 (0.122)
ln_size	-0.192**** (0.032)	-0.176**** (0.037)	-0.159**** (0.03)	-0.141**** (0.038)	-0.150**** (0.032)	-0.157**** (0.032)	-0.134**** (0.032)	-0.175**** (0.032)
ln_age	0.015 (0.038)	-0.02 (0.04)	0.02 (0.034)	-0.004 (0.036)	0.016 (0.034)	-0.006 (0.033)	-0.018 (0.034)	0.02 (0.036)

Table 5.9: Results from IVPR of DIC technologies (N=1412… con'td and end)

inress	0.021 (0.103)	0.07 (0.108)	0.001 (0.093)	-0.09 (0.097)	0.119 (0.1)	0.108 (0.096)	-0.071 (0.091)	0.052 (0.102)
inlab	0.069 (0.142)	0.155 (0.148)	0.035 (0.119)	0.046 (0.123)	0.084 (0.123)	0.118 (0.119)	-0.001 (0.114)	0.104 (0.139)
inscal	-0.175 (0.12)	-0.105 (0.128)	-0.109 (0.111)	0.029 (0.124)	-0.009 (0.118)	0.129 (0.121)	-0.106 (0.111)	-0.127 (0.118)
inspec	-0.143 (0.131)	-0.201 (0.13)	-0.208* (0.109)	0.082 (0.133)	-0.185* (0.112)	-0.102 (0.111)	-0.274*** (0.106)	-0.165 (0.12)
insci	-0.072 (0.191)	0.073 (0.203)	-0.351*** (0.134)	0.311* (0.185)	-0.418*** (0.133)	-0.161 (0.137)	-0.280** (0.135)	-0.384*** (0.142)
constant	-1.042**** (0.235)	-0.860*** (0.281)	-1.200**** (0.188)	-0.861*** (0.269)	-1.271**** (0.195)	-1.143**** (0.211)	-1.324**** (0.18)	-1.044**** (0.223)
First Stage OLS Regression – Dependent variable = ln_Index_DIC								
Concurrent Eng.	0.128**** (0.031)	0.128**** (0.031)	0.128**** (0.031)	0.129**** (0.031)	0.128**** (0.031)	0.127**** (0.031)	0.129**** (0.031)	0.128**** (0.031)
Cross-funct. Teams	0.117**** (0.029)	0.116**** (0.029)	0.116**** (0.029)	0.116**** (0.029)	0.117**** (0.029)	0.116**** (0.029)	0.117**** (0.029)	0.117**** (0.029)
Collab-uni&gvt	0.036 (0.032)	0.034 (0.032)	0.035 (0.032)	0.032 (0.032)	0.034 (0.032)	0.036 (0.032)	0.034 (0.032)	0.035 (0.032)
Collab-firms	0.065** (0.028)	0.064** (0.028)	0.064** (0.028)	0.063** (0.028)	0.064** (0.028)	0.065** (0.028)	0.064** (0.028)	0.065** (0.028)
CTI-Benchmarking	0.057 (0.036)	0.058 (0.036)	0.057 (0.036)	0.058 (0.036)	0.058 (0.036)	0.057 (0.036)	0.058 (0.036)	0.057 (0.036)
Sustain. Dev-ESP	0.128*** (0.045)	0.129*** (0.045)	0.129*** (0.045)	0.130*** (0.045)	0.128*** (0.045)	0.130*** (0.045)	0.129*** (0.045)	0.128*** (0.045)
PDM & LCM	0.112*** (0.036)	0.110*** (0.036)	0.112*** (0.036)	0.110*** (0.036)	0.111*** (0.036)	0.113*** (0.036)	0.110*** (0.036)	0.112*** (0.036)
Outsourcing	0.016 (0.028)	0.014 (0.028)	0.015 (0.028)	0.013 (0.028)	0.014 (0.028)	0.015 (0.028)	0.014 (0.028)	0.015 (0.028)
ln_size	0.093**** (0.01)	0.094**** (0.01)	0.094**** (0.01)	0.094**** (0.01)	0.094**** (0.01)	0.093**** (0.01)	0.094**** (0.01)	0.093**** (0.01)
ln_age	-0.007 (0.013)	-0.007 (0.013)	-0.007 (0.013)	-0.007 (0.013)	-0.007 (0.013)	-0.007 (0.013)	-0.007 (0.013)	-0.007 (0.013)
inress	0.048 (0.037)	0.047 (0.037)	0.048 (0.037)	0.046 (0.037)	0.047 (0.037)	0.049 (0.037)	0.046 (0.037)	0.048 (0.037)
inlab	0.096** (0.042)	0.096** (0.042)	0.096** (0.042)	0.096** (0.042)	0.096** (0.042)	0.096** (0.042)	0.096** (0.042)	0.096** (0.042)
inscal	0.119*** (0.043)	0.119*** (0.043)	0.120*** (0.043)	0.120*** (0.043)	0.119*** (0.043)	0.120*** (0.043)	0.119*** (0.043)	0.119*** (0.043)
inspec	0.124*** (0.042)	0.122*** (0.042)	0.123*** (0.042)	0.122*** (0.042)	0.122*** (0.042)	0.124*** (0.042)	0.122*** (0.042)	0.123*** (0.042)
insci	0.159*** (0.053)	0.158*** (0.053)	0.158*** (0.053)	0.157*** (0.053)	0.158*** (0.053)	0.158*** (0.053)	0.158*** (0.053)	0.159*** (0.053)
ln_Index_Measures	0.095*** (0.03)	0.121**** (0.031)	0.105**** (0.028)	0.130**** (0.031)	0.119**** (0.029)	0.089*** (0.031)	0.122**** (0.028)	0.100**** (0.03)
CAPEX_DIC[a]	0.027**** (0.006)	0.023**** (0.007)	0.023**** (0.006)	0.019*** (0.007)	0.025**** (0.006)	0.021**** (0.006)	0.024**** (0.006)	0.026**** (0.006)
Empl Recruit	0.093**** (0.024)	0.090**** (0.026)	0.102**** (0.023)	0.095**** (0.026)	0.087**** (0.024)	0.115**** (0.024)	0.086**** (0.023)	0.093**** (0.024)
constant	0.626**** (0.064)	0.604**** (0.064)	0.617**** (0.063)	0.596**** (0.064)	0.606**** (0.064)	0.631**** (0.065)	0.603**** (0.063)	0.621**** (0.064)
N	1412	1412	1412	1412	1412	1412	1412	1412
ll	-1317.647	-1486.361	-1631.47	-1752.659	-1687.595	-1868.347	-1726.799	-1444.705
chi2	638.761****	365.608****	464.169****	263.269****	385.745****	169.816****	496.236****	474.791****
chi2_exog	26.493****	12.383****	32.405****	8.196***	23.239****	16.958****	28.997****	26.486****
overid	0.056	0.278[b]	0.356	0.619	0.109	0.406[c]	0.106	0.092
* p<0.1, ** p<0.05, *** p<0.01, **** p<0.001								

a: The CAPEX variable used in this regression is a percentage of total expenditures on advanced technologies. The total amount of CAPEX has been tested and no major changes in coefficients and significance have been observed, besides those enumerated below

b: This coefficient becomes lower 0.039, suggesting the model is over-specified

c: This coefficient becomes lower 0.047, suggesting the model is over-specified.

5.2.3 Results of the PF technologies regressions

The results from the IVPR of PF technologies are presented in Table 5.10. It used the same sample of companies as for DIC technologies. The first stage regression highlights an endogenous effect. The instrumental variables have a positive and statistically significant effect across most models. However, testing against marketing innovation shows that the measures to counter obstacles do not have a significant effect on the adoption of technologies. Furthermore, CAPEX is not significant in firms having developed product innovations[15]. This could be due to the fact that investments in new technologies were not a main factor for highly innovative firms. In fact, companies who want to create new products may adopt these technologies based on other criteria independently of the price. The literature has identified many determinants of advanced manufacturing technology adoption: (1) cost, (2) organizational (3) technological, (4) environmental. For instance, the cost dimension is critical in the case of adopting 3D printing technologies because various forms of investments require to be taken into consideration, such as related hardware, software and system integration (Allen, 2006; Baumers, Dickens, Tuck, & Hague, 2016; Heath, 2015; D. Thomas, 2016). The organizational element has previously been discussed when the resource-based-view of the firm was presented in the survey of the literature. The technological factor is also important because of the incorporation that needs to happen between PF technologies and DIC technologies. This has been mentioned beforehand when referencing technological proximity because technology that is already adopted influences new technology adoption. For instance, 3D printers can be combined with computer-aided design (CAD) software and other digital techniques from

[15] The CAPEX variable used in these regressions represented the percentage of capital expenditures in each family of technologies (in DIC and PF in this case). When variable was substituted to include the amount of CAPEX spent instead, the instruments that were not significant became positive and significant. This is the case for the CAPEX_PF variable in Model D (product innovation) and the ln_Index_Measures in Model F (marketing innovation).

the medical field such as magnetic resonance imaging (Berman, 2012; Petrick & Simpson, 2013; Quan et al., 2015). Therefore, companies that have a complex technology infrastructure will be more likely to adopt PF technologies. Finally, the environmental aspect can act as a way to influence firms to purchase new technologies to gain a competitive advantage (Jeyaraj, Rottman, & Lacity, 2006). In the case of PF technologies, innovative firms will take advantage of external competitive pressure by being forced to adopt new technologies (Pei, Conner, Manogharan, & Meyers, 2015) in order to increase supply chain visibility and operational efficiency (Y.-M. Wang et al., 2010). In light of all these factors, firms that are focussed on product innovation through new advanced manufacturing techniques might be disregarding cost as an important dimension to the adoption of these technologies. Because companies have already adopted design technologies, where cost was already factored in, it is possible that PF technology adoption was influenced by other determinants such as outside pressure and integration with technology already in place. In other words, technological proximity might be more important than cost for firms looking to adopt advanced PF technologies in order to develop new products.

The second stage suggests similar findings to previous technologies. As anticipated, the number of adopted PF technologies had a positive and significant coefficient ($p<0.001$) when tested against all types of innovations. Collaboration and OI practices are not significant for all models. Similar results were found with the variables of concurrent engineering and cross-functional teams. The former had no significant effect while the latter has a positive and a statistically significant effect when it comes to product innovation. CFT was expected to have a positive effect on product innovation as with other technologies. The fact that no significant effect was found for collaboration strategies could be due to companies emphasizing technology adoption as their main source of competitive advantage that is driving innovation. As a consequence, collaboration may not have a significant effect if companies are adopting technologies to gain a competitive advantage of their competitors.

In terms of control variables, size plays a negative role when it comes to innovation across all models. In fact, smaller firms are more inclined to introduce innovations. Negative coefficients are observed for all industries. The coefficients of inress, inlab, inscal, inspec and insci are all negative and statistically significant, suggesting that in some specific types of innovation, some sectors have a negative effect on innovation propensity when compared to the service sector. However, one common point is that the coefficients are not significant when tested against product innovation, except for resource-intensive industries (p<0.01) in which case the coefficient is negative. While it is anticipated that the manufacturing sectors tend to have a lower innovation propensity in non-technological innovations, it is counterintuitive to think that services adopting PF technologies had a higher probability to develop new products. However, the service sector is prominent in product innovation services (Oke, 2007), which could be the reason why the manufacturing sector has a negative impact on innovation when compared to services.

Table 5.10: Results from IVPR of PF technologies (N=1412)[16]

MODELS	A	B	C	D	E	F	G	H
	allinno	techinno	nontechinno	prodinno	procinno	markinno	orginno	businno
Second Stage Probit Regression – Dependent variable = Type of innovation (models A to H)								
ln_Index_PF	1.781**** (0.078)	1.554**** (0.176)	1.584**** (0.106)	1.144**** (0.272)	1.575**** (0.131)	1.317**** (0.176)	1.530**** (0.124)	1.656**** (0.101)
Concurrent Eng.	0.016 (0.138)	0.217 (0.166)	-0.088 (0.096)	0.127 (0.128)	-0.025 (0.107)	-0.152* (0.088)	-0.081 (0.097)	-0.079 (0.107)
Cross-funct. Teams	-0.085 (0.089)	0.041 (0.106)	-0.107 (0.076)	0.268** (0.117)	-0.141* (0.076)	-0.140* (0.074)	-0.094 (0.077)	-0.143* (0.079)
Collab-uni&gvt	-0.035 (0.102)	-0.088 (0.1)	-0.091 (0.083)	-0.129 (0.09)	-0.092 (0.085)	-0.145* (0.078)	-0.078 (0.083)	-0.07 (0.091)
Collab-firms	0.02 (0.08)	0.073 (0.089)	-0.008 (0.071)	0.078 (0.081)	0.051 (0.076)	0.011 (0.07)	0.045 (0.073)	0.006 (0.076)
CTI-Benchmarking	-0.088 (0.107)	0.041 (0.124)	-0.008 (0.097)	0.145 (0.116)	0 (0.099)	0.034 (0.095)	0.018 (0.098)	-0.04 (0.103)
Sustain. Dev-ESP	0.142 (0.137)	0.209 (0.148)	-0.065 (0.114)	-0.083 (0.126)	0.156 (0.12)	0.078 (0.11)	-0.032 (0.113)	0.064 (0.123)
PDM & LCM	0.166 (0.14)	0.186 (0.136)	0.096 (0.103)	0.158 (0.113)	0.047 (0.1)	0.152 (0.102)	0.11 (0.103)	0.066 (0.11)
Outsourcing	-0.015 (0.085)	0.118 (0.102)	-0.001 (0.076)	0.104 (0.09)	-0.023 (0.076)	0.036 (0.077)	0.043 (0.08)	-0.01 (0.081)
ln_size	-0.118**** (0.027)	-0.111**** (0.03)	-0.096**** (0.026)	-0.104**** (0.031)	-0.090*** (0.028)	-0.112**** (0.026)	-0.076*** (0.028)	-0.105**** (0.027)
ln_age	0.006 (0.035)	-0.024 (0.038)	0.011 (0.032)	-0.009 (0.036)	0.01 (0.033)	-0.01 (0.032)	-0.021 (0.032)	0.011 (0.034)
inress	-0.234** (0.097)	-0.156 (0.111)	-0.215** (0.093)	-0.238** (0.104)	-0.111 (0.104)	-0.086 (0.103)	-0.267*** (0.09)	-0.185* (0.1)
inlab	-0.573**** (0.14)	-0.414** (0.18)	-0.525**** (0.132)	-0.355* (0.183)	-0.477*** (0.146)	-0.363** (0.154)	-0.535**** (0.132)	-0.498**** (0.148)
inscal	-0.326*** (0.11)	-0.247** (0.125)	-0.246** (0.108)	-0.08 (0.134)	-0.159 (0.118)	-0.02 (0.126)	-0.236** (0.109)	-0.270** (0.112)
inspec	-0.572**** (0.122)	-0.561**** (0.136)	-0.561**** (0.111)	-0.197 (0.173)	-0.544**** (0.117)	-0.416**** (0.126)	-0.602**** (0.108)	-0.546**** (0.118)
insci	-0.225 (0.172)	-0.072 (0.199)	-0.446**** (0.129)	0.186 (0.202)	-0.506**** (0.129)	-0.276** (0.135)	-0.379*** (0.13)	-0.472**** (0.133)

[16] The observed VIF coefficients range from 1.03 to 1.23 with a mean of 1.16.

Table 5.10: Results from IVPR of PF technologies (N=1412… con'td and end)

constant	0.523*** (0.166)	0.516*** (0.167)	0.296** (0.14)	0.148 (0.156)	0.202 (0.143)	0.054 (0.144)	0.154 (0.14)	0.476*** (0.153)
First Stage OLS Regression – Dependent variable = ln_Index_PF								
Concurrent Eng.	0.164**** (0.037)	0.164**** (0.037)	0.164**** (0.037)	0.165**** (0.037)	0.165**** (0.037)	0.164**** (0.037)	0.165**** (0.037)	0.164**** (0.037)
Cross-funct. Teams	0.110*** (0.034)	0.108*** (0.034)	0.108*** (0.034)	0.107*** (0.034)	0.109*** (0.034)	0.108*** (0.034)	0.109*** (0.034)	0.109*** (0.034)
Collab-uni&gvt	0.104*** (0.038)	0.101*** (0.038)	0.102*** (0.038)	0.100*** (0.038)	0.101*** (0.038)	0.104*** (0.038)	0.101*** (0.038)	0.103*** (0.038)
Collab-firms	0.031 (0.033)	0.029 (0.033)	0.03 (0.033)	0.028 (0.033)	0.03 (0.033)	0.03 (0.033)	0.03 (0.033)	0.031 (0.033)
CTI-Benchmarking	0.071* (0.043)	0.071* (0.043)	0.071* (0.043)	0.072* (0.043)	0.072* (0.043)	0.071* (0.043)	0.072* (0.043)	0.071* (0.043)
Sustain. Dev-ESP	-0.043 (0.054)	-0.042 (0.054)	-0.043 (0.054)	-0.041 (0.054)	-0.043 (0.054)	-0.041 (0.054)	-0.043 (0.054)	-0.043 (0.054)
PDM & LCM	0.070* (0.042)	0.069 (0.042)	0.069 (0.042)	0.069 (0.042)	0.069 (0.042)	0.072* (0.042)	0.068 (0.042)	0.070* (0.042)
Outsourcing	0.063* (0.034)	0.061* (0.033)	0.062* (0.033)	0.060* (0.033)	0.061* (0.034)	0.063* (0.033)	0.061* (0.034)	0.063* (0.034)
ln_size	0.064**** (0.012)	0.065**** (0.012)	0.065**** (0.012)	0.066**** (0.012)	0.065**** (0.012)	0.064**** (0.012)	0.065**** (0.012)	0.064**** (0.012)
ln_age	-0.003 (0.016)	-0.002 (0.016)	-0.003 (0.016)	-0.002 (0.016)	-0.003 (0.016)	-0.002 (0.016)	-0.003 (0.016)	-0.003 (0.016)
inress	0.183**** (0.044)	0.181**** (0.044)	0.182**** (0.044)	0.181**** (0.044)	0.181**** (0.044)	0.184**** (0.044)	0.180**** (0.044)	0.182**** (0.044)
inlab	0.439**** (0.049)	0.439**** (0.049)	0.439**** (0.049)	0.439**** (0.049)	0.439**** (0.049)	0.439**** (0.049)	0.439**** (0.049)	0.439**** (0.049)
inscal	0.208**** (0.051)	0.210**** (0.051)	0.210**** (0.051)	0.211**** (0.051)	0.209**** (0.051)	0.210**** (0.051)	0.209**** (0.051)	0.209**** (0.051)
inspec	0.362**** (0.05)	0.360**** (0.05)	0.361**** (0.05)	0.360**** (0.05)	0.360**** (0.05)	0.363**** (0.05)	0.360**** (0.05)	0.361**** (0.05)
insci	0.247**** (0.062)	0.246**** (0.062)	0.246**** (0.062)	0.244**** (0.062)	0.246**** (0.062)	0.245**** (0.062)	0.246**** (0.062)	0.247**** (0.062)
ln_Index_Measures	0.059** (0.03)	0.084** (0.033)	0.074*** (0.028)	0.089*** (0.034)	0.088*** (0.03)	0.043[c] (0.031)	0.093*** (0.029)	0.067** (0.029)
CAPEX_PF[a]	0.023**** (0.006)	0.016** (0.007)	0.018*** (0.006)	0.01[b] (0.008)	0.020*** (0.006)	0.014** (0.007)	0.019*** (0.006)	0.022**** (0.006)
Empl Recruit	0.114**** (0.031)	0.122**** (0.032)	0.122**** (0.029)	0.133**** (0.032)	0.108**** (0.031)	0.145**** (0.03)	0.104**** (0.03)	0.113**** (0.031)
constant	-0.209*** (0.074)	-0.231*** (0.074)	-0.223*** (0.073)	-0.236*** (0.075)	-0.234*** (0.074)	-0.196*** (0.074)	-0.238*** (0.073)	-0.216*** (0.074)
N	1412	1412	1412	1412	1412	1412	1412	1412
ll	-1551.288	-1724.566	-1867.09	-1986.027	-1925.627	-2099.929	-1965.256	-1682.111
chi2	850.693****	455.083****	615.827****	304.014****	522.109****	231.353****	620.82****	655.291****
chi2_exog	29.064****	13.319****	32.836****	7.653***	22.204****	20.692****	27.555****	28.002****
overid	0.056	0.278	0.356	0.619	0.109	0.406	0.106	0.092
* p<0.1, ** p<0.05, *** p<0.01, **** p<0.001								

a: The CAPEX variable used in this regression is a percentage of total expenditures on advanced technologies. The total amount of CAPEX has been tested and no major changes in coefficients and significance have been observed, besides those enumerated below

b c: This coefficient becomes significant.

5.2.4 Results of the MHSCL technologies regressions

Table 8.3 in Appendix A presents the descriptive statistics of the sample of firms that have adopted MHSCL technologies. While the exogeneity test is rejected ($p<0.001$), the overidentification test (overid) shows a p value that is very low, which suggests that the instruments are not valid in this context. Other instruments (e.g. obstacles to innovation) were used but it was not possible to correct the model specification in this case. It is difficult to explain why the overidentification test is not valid considering that for all the other three categories of technologies, the model was correctly specified with the same instruments. This could be due to the fact that MHSCL technologies have been the most adopted amongst firms and these firms could be spread across different sectors, indicating the heterogeneity of the sample. The results of the IVPR for MHSCL technologies are presented in table Table 5.11, but they need to be interpreted with caution as the models are not correctly specified due to the instruments utilized.

Accounting for endogeneity, all models result in a positive and significant effect of the index of adopted MHSCL technologies ($p<0.001$) on the propensity to innovate, regardless of the type of innovation. In other words, the more advanced technologies adopted, the higher the propensity to innovate. It should also be noted that innovation is impacted both by collaboration with universities and governments and collaboration with firms. Collaboration with universities and governments (Collab-uni&gvt) had a positive and significant effect as well. This was not the case when considering collaboration with other companies (Collab-firms), except for the propensity to generate product innovations (Model D). This result was expected because a greater frequency of interactions with suppliers and customers leads to a higher probability of product innovation (Jordan & O'Leary, 2007). Moreover, firms collaborating with other firms within the supply chain are more likely to develop new products (Schleimer & Faems, 2016).

Other practices such as concurrent engineering and cross-functional design teams also yield positive and statistically significant results. Interestingly, cross-functional design teams are important for product innovation ($p<0.001$) but not for process, organizational and marketing innovations. This practice also requires codified knowledge to be shared across different teams within the same firm. However, categorizing innovation into technical and non-technical innovation categories, the effect becomes statistically significant. The same is observed using the new business process innovation in model H ($p<0.05$). While cross-functional design teams do not seem to impact specific type of innovation, it does affect the propensity to innovate when viewed in categories. This can be explained by the fact that some firms might only develop some type of innovations based on their business model. When combining the types of innovation, the percentage of firms innovating increases, which confers a consensus on the importance of cross-functional design teams. The positive effects of CE and CFT are in line with the previous literature as was mentioned above for the other families of technologies.

This next paragraph discusses the effects of the control variables used in this study. The natural logarithm was used to normalize both age and size variables. Size has a negative effect on the propensity to innovate regardless of the innovation type, while age does not have any effect. In terms of industry effects, some sectors tend to have a positive influence on the propensity to innovate, in particular those in resource-intensive, labour-intensive and specialized suppliers (e.g. inress, inlab, inspec). While resource-intensive and labour-intensive sectors exhibit positive effects in most models, specialized suppliers have a higher propensity to introduce product innovations.

Table 5.11: Results from IVPR of MHSCL technologies (N=2389) [17]

MODELS	A	B	C	D	E	F	G	H
	allinno	techinno	nontechinno	prodinno	procinno	markinno	orginno	businno
Second Stage Probit Regression – Dependent variable = Type of innovation (models A to H)								
ln_Index_MHSCL	2.365**** (0.086)	2.243**** (0.111)	2.353**** (0.079)	1.472**** (0.287)	2.335**** (0.083)	2.037**** (0.15)	2.369**** (0.074)	2.367**** (0.077)
Collab-firms	0.015 (0.064)	0.055 (0.064)	-0.013 (0.057)	0.146** (0.071)	0.03 (0.058)	0.028 (0.06)	0.02 (0.057)	-0.004 (0.06)
Collab-uni&gvt	0.263*** (0.081)	0.262**** (0.077)	0.156** (0.066)	0.201*** (0.074)	0.198*** (0.066)	0.093 (0.065)	0.129** (0.064)	0.188*** (0.071)
Concurrent Eng.	0.299**** (0.081)	0.411**** (0.084)	0.218*** (0.067)	0.390**** (0.077)	0.268**** (0.067)	0.141** (0.065)	0.221**** (0.065)	0.246**** (0.071)
Cross-funct. Teams	0.197** (0.078)	0.198*** (0.073)	0.127** (0.065)	0.367**** (0.079)	0.061 (0.061)	0.069 (0.062)	0.096 (0.061)	0.166** (0.07)
Outsourcing	0.231*** (0.071)	0.284**** (0.071)	0.158*** (0.06)	0.301**** (0.069)	0.165*** (0.059)	0.175*** (0.06)	0.146** (0.057)	0.176*** (0.063)
CTI-Benchmarking	0 (0.088)	0.057 (0.088)	0.001 (0.078)	0.136 (0.092)	0.039 (0.078)	0.014 (0.077)	0.021 (0.076)	0.028 (0.083)
Sustain. Dev-ESP	-0.169 (0.107)	-0.166 (0.104)	-0.184** (0.094)	-0.242** (0.106)	-0.181* (0.092)	-0.153 (0.094)	-0.188** (0.091)	-0.173* (0.099)

[17] The average VIF is 1.16 (ranges from 1.03 to 1.30) for all variables of the first stage, indicating that there is no collinearity.

Table 5.11: Results from IVPR of MHSCL technologies (N=2389… con'td)

PDM & LCM	-0.146 (0.096)	-0.101 (0.094)	-0.192** (0.08)	0.105 (0.111)	-0.239*** (0.076)	-0.173** (0.081)	-0.127 (0.081)	-0.203** (0.084)
ln_size	-0.243**** (0.021)	-0.228**** (0.023)	-0.246**** (0.02)	-0.172**** (0.034)	-0.228**** (0.02)	-0.247**** (0.022)	-0.233**** (0.02)	-0.248**** (0.02)
ln_age	0.032 (0.025)	0.022 (0.026)	0.022 (0.024)	-0.009 (0.029)	0.043* (0.024)	0.01 (0.025)	0.007 (0.024)	0.036 (0.024)
inress	0.169** (0.07)	0.194*** (0.07)	0.148** (0.067)	0.167** (0.074)	0.191*** (0.067)	0.184*** (0.069)	0.104 (0.065)	0.163** (0.068)
inlab	0.212** (0.093)	0.199** (0.088)	0.097 (0.08)	0.256*** (0.092)	0.183** (0.083)	0.138* (0.083)	0.085 (0.079)	0.179** (0.087)
inscal	-0.029 (0.081)	0.05 (0.082)	-0.073 (0.078)	0.134 (0.089)	0.113 (0.079)	0.028 (0.08)	-0.072 (0.078)	-0.021 (0.079)
inspec	0.210** (0.097)	0.183* (0.094)	0.032 (0.085)	0.322*** (0.101)	0.116 (0.085)	-0.038 (0.088)	0.062 (0.084)	0.105 (0.088)
insci	0.044 (0.122)	0.111 (0.121)	-0.124 (0.101)	0.351*** (0.134)	-0.13 (0.099)	-0.059 (0.102)	-0.165* (0.099)	-0.083 (0.106)
constant	-1.696**** (0.14)	-1.778**** (0.138)	-1.757**** (0.125)	-1.373**** (0.24)	-2.026**** (0.111)	-1.650**** (0.155)	-1.937**** (0.112)	-1.731**** (0.128)
First Stage OLS Regression – Dependent variable = ln_Index_MHSCL								
Concurrent Eng.	-0.041* (0.022)	-0.040* (0.022)	-0.041* (0.022)	-0.039* (0.022)	-0.040* (0.022)	-0.040* (0.022)	-0.040* (0.022)	-0.041* (0.022)
Cross-funct. Teams	0.012 (0.021)	0.012 (0.021)	0.012 (0.021)	0.013 (0.021)	0.012 (0.021)	0.012 (0.021)	0.012 (0.021)	0.012 (0.021)
Collab-uni&gvt	-0.031 (0.022)	-0.032 (0.022)	-0.032 (0.022)	-0.032 (0.022)	-0.032 (0.022)	-0.032 (0.022)	-0.031 (0.022)	-0.031 (0.022)
Collab-firms	0.042** (0.019)	0.042** (0.019)	0.041** (0.019)	0.042** (0.019)	0.042** (0.019)	0.042** (0.019)	0.042** (0.019)	0.042** (0.019)
CTI-Benchmarking	0.037 (0.025)	0.037 (0.025)	0.036 (0.025)	0.037 (0.025)	0.037 (0.025)	0.036 (0.025)	0.037 (0.025)	0.037 (0.025)
Sustain. Dev-ESP	0.107**** (0.031)	0.107**** (0.031)	0.107**** (0.031)	0.107**** (0.031)	0.107**** (0.031)	0.107**** (0.031)	0.107**** (0.031)	0.107**** (0.031)
PDM & LCM	0.139**** (0.025)	0.139**** (0.025)	0.138**** (0.025)	0.139**** (0.025)	0.139**** (0.025)	0.138**** (0.025)	0.139**** (0.025)	0.139**** (0.025)
Outsourcing	-0.005 (0.019)	-0.004 (0.019)	-0.005 (0.019)	-0.003 (0.019)	-0.005 (0.019)	-0.005 (0.019)	-0.005 (0.019)	-0.005 (0.019)
ln_size	0.099**** (0.006)	0.099**** (0.006)	0.099**** (0.006)	0.100**** (0.006)	0.099**** (0.006)	0.099**** (0.006)	0.099**** (0.006)	0.099**** (0.006)
ln_age	-0.020** (0.008)	-0.020** (0.008)	-0.020** (0.008)	-0.019** (0.008)	-0.020** (0.008)	-0.020** (0.008)	-0.020** (0.008)	-0.020** (0.008)
inress	-0.024 (0.023)	-0.025 (0.023)	-0.024 (0.023)	-0.026 (0.023)	-0.024 (0.023)	-0.025 (0.023)	-0.024 (0.023)	-0.024 (0.023)
inlab	0.012 (0.028)	0.014 (0.028)	0.013 (0.028)	0.015 (0.028)	0.013 (0.028)	0.014 (0.028)	0.013 (0.028)	0.013 (0.028)
inscal	0.004 (0.028)	0.004 (0.028)	0.005 (0.028)	0.004 (0.028)	0.004 (0.028)	0.005 (0.028)	0.004 (0.028)	0.004 (0.028)
inspec	-0.018 (0.03)	-0.015 (0.03)	-0.017 (0.03)	-0.013 (0.03)	-0.016 (0.03)	-0.016 (0.03)	-0.016 (0.03)	-0.017 (0.03)
insci	0.069** (0.035)	0.070** (0.035)	0.070** (0.035)	0.071** (0.035)	0.070** (0.035)	0.070** (0.035)	0.070** (0.035)	0.070** (0.035)
ln_Index_Measures	0.073**** (0.017)	0.083**** (0.018)	0.081**** (0.016)	0.096**** (0.021)	0.079**** (0.016)	0.086**** (0.018)	0.078**** (0.015)	0.074**** (0.016)
CAPEX_MHSCL[a]	0.021**** (0.004)	0.023**** (0.004)	0.021**** (0.004)	0.024**** (0.004)	0.023**** (0.004)	0.023**** (0.004)	0.023**** (0.004)	0.022**** (0.004)
Empl Recruit	0.057**** (0.014)	0.041*** (0.014)	0.053**** (0.012)	0.023 (0.019)	0.045**** (0.012)	0.042*** (0.014)	0.045**** (0.012)	0.054**** (0.013)
constant	0.699**** (0.04)	0.688**** (0.039)	0.692**** (0.039)	0.675**** (0.04)	0.691**** (0.039)	0.686**** (0.04)	0.692**** (0.039)	0.697**** (0.039)
constant	-1.479****	-1.225****	-1.456****	-0.624****	-1.377****	-1.035****	-1.451****	-1.516****
constant	-0.946****	-0.947****	-0.946****	-0.948****	-0.947****	-0.947****	-0.947****	-0.946****
N	2389	2389	2389	2389	2389	2389	2389	2389
ll	-2046.199	-2292.639	-2392.857	-2547.899	-2496.611	-2675.406	-2495.336	-2181.058
chi2	2048.296****	1679.372****	1953.805****	593.129****	1914.089****	600.665****	2206.45****	2117.135****

Table 5.11: Results from IVPR of MHSCL technologies (N=2389… con’td and end)

chi2_exog	71.434****	63.043****	92.188****	14.328****	92.958****	48.141****	106.316****	92.101****
overid	0	0.001	0	0.001	0.002	0.001	0.003	0
* p<0.1, ** p<0.05, *** p<0.01, **** p<0.001								

a: The CAPEX variable used in this regression is a percentage of total expenditures on advanced technologies. The total amount of CAPEX has been tested and no major changes in coefficients and significance have been observed.

5.3 Summary and conclusions

The results showed that all models rejected the exogenous hypothesis, suggesting that there was an endogenous effect in the specified model. The same instrumental variables were used for all categories of technologies. However, testing for overidentification highlighted that the model for MHSCL technologies has not been correctly specified. Other variables were used, such as the obstacles to adopting new technologies, but the overidentification test still yielded a p value under 0.05. This was also the case in models involving BI technologies, specifically when testing against non-technical (p=0.015) and marketing (p=0.051) innovation. However, the overidentification test was rejected when testing against the new business process definition of innovation, regrouping process, marketing and organizational innovations. These outcomes need to be interpreted with caution.

For all the categories of technologies, the three instrumental variables used were positive and significant. Measures to counter adoption obstacles, capital invested and recruiting new employees all seem to increase the number of adopted technologies. Unsurprisingly, recruiting new employees pertaining to the adoption of these new technologies have a positive impact on their adoption because technical “know-how” is a good motivator to adopt new technologies (Sulaiman et al., 2012). Furthermore, they have enough resources to help their supply chain partners go in the same direction (Mabert et al., 2003).

Innovation is also impacted by collaboration and OI practices. Collaboration with universities and governments had a positive effect that is significant with companies having adopted MHSCL and BI technologies. However, this was not the case with DIC and PF technologies. The same results were observed with collaboration with other firms. Only MHSCL and BI technology adopters have found a positive impact on the propensity to innovate. Other types of technology adopters have not had a significant effect. In other words, hypotheses H1 and H2 have been validated for MHSCL and BI adopters only.

Cross-functional teams (CFT) are also significant and play a positive role in general. This influence was only observed on MHSCL and BI technology adopters. In the case of DIC and PF technologies, CFT had a positive and significative coefficient when it comes to product innovation, which is expected. However, that effect was negative when testing against process and marketing innovations. As expected, innovation performance of functionally organized projects is positively impacted by CFT (Blindenbach-Driessen, 2014). While this validates H3 partially, it would be interesting to understand why CFT can play a negative role when tested against process and marketing innovations individually. This effect was not seen in the MHSCL and BI samples. On the contrary, a positive effect was observed in the models pertaining to non-technical innovation and the new Oslo Manual definition of non-technical innovation.

Another form of cooperation consisted of outsourcing certain activities to partners or other companies. Similar to the other hypotheses tested, there is significant effect when analyzing the DIC and PF samples. On the other hand, the MHSCL and BI samples of firms that outsourced their activities have seen a positive and significative impact on their propensity to innovate. Through outsourcing, companies can gain access to new sources of information (Lewin et al., 2009). This is also the case when outsourcing R&D activities (Paju, 2007), which in turn can lead to an increased innovation performance. Similarly, H4 is partially validated, only for MHSCL and BI technology adopters.

Results from the second stage probit regressions highlights that regardless of the type of innovation, all models are significant in terms of the index of adopted technologies ($p<0.001$), for all categories. In fact, the more advanced technologies are adopted, the higher the propensity to innovate. The results validate hypotheses 5a, 5b and 5c regarding all categories of technologies. SCT (MHSCL technologies) adoption allows firms to gain a competitive advantage and creates value for shareholders (Mishra et al., 2013; Yao et al., 2009). For example, delivery performance can be enhanced because it increases a firm's knowledge capability and absorptive capacity (Setia & Patel, 2013). Moreover, the adoption of SCT contributes to increasing visibility in the supply chain, resulting in higher collaboration and coordination in the supply chain network (Fawcett et al., 2007). BI technologies can also provide a competitive advantage to firms though connectivity and new data that can be used (M. E. Porter & Heppelmann, 2015). It can be argued this can increase a firm's propensity to innovate. AMTs (including DIC and PF technologies) can also increase a firm's innovation propensity. For instance, the propensity to introduce process and product innovations may be increased following the adoption of 3D printing technologies (Niaki & Nonino, 2017). This validates H5a, H5b and H5c.

Some sectoral patterns could be noted as well. For BI technologies, manufacturing firms showed a positive and significant coefficient when compared with services. This was especially true with product and process innovation. In the case of DIC and PF technologies, there was no statistical significance across most sectors. Interestingly, the science-based industries (high-tech manufacturing firms) had a negative impact on process and non technical innovation when compared to services. This was also the case when tested against the recent definition of business process innovation. This could be explained by the fact that firms adopting advanced manufacturing technologies might be solely focussed on product innovation to the point of hindering their performance in the development of new marketing or organizational strategies.

Table 5.12: Summary of hypotheses validation

Hypotheses	Any Innovation	Technical innovation	Non-Technical	Business process
MSHCL Technologies				
H1: Collaboration with other firms	✓	✓	✓	✓
H2: Collaboration with universities and government	✓	✓	✓	✓
H3: Cross-functional teams	✓	✓	✓	✓
H4: Outsourcing	✓	✓	✓	✓
H5a: Number of technologies	✓	✓	✓	✓

Table 5.12: Summary of hypotheses validation (con'td and end)

BI Technologies				
H1: Collaboration with other firms	✓	✓	✓	✓
H2: Collaboration with universities and government	✓	✓	✓	✓
H3: Cross-functional teams	✓	✓	×	×
H4: Outsourcing	✓	✓	×	✓
H5b: Number of technologies	✓	✓	✓	✓
DIC and PF Technologies				
H1: Collaboration with other firms	×	×	×	×
H2: Collaboration with universities and government	×	×	×	×
H3: Cross-functional teams	×	✓[18]	✓	✓[19]
H4: Outsourcing	×	×	×	×
H5c: DIC and PF technologies	✓	✓	✓	✓

[18] Positive coefficient that is significant when tested against product innovation.

[19] Negative coefficient that is significant when tested against process and marketing innovations.

Table 5.13: Summary of other tests performed by technology

Other tests performed by technology	MHSCL	BI	DIC	PF
Collinearity	✓	✓	✓	✓
Endogeneity	✓	✓	✓	✓
Overidentification	×	✓	✓	✓

Despite validating hypotheses, there are some limits to the research. First, despite rejecting the overidentification test for three out of the four categories of technologies specified, it will be important to identify better instruments in the future. One potential instrument that wasn't tested is the combination of cross-dummy variables of the obstacles to adoption and the measures adopted to counter these obstacles. This can be a future research proposal. It would also be interesting to complement this study with interviews of specific sectors having adopted DIC and PF technologies specifically. Firms who adopted these technologies do not seem to be impacted by OI practices. Furthermore, cross-functional teams seemed to play a negative role in non-technical innovations. While CFT is known to be useful for product innovation, it is somewhat counterintuitive that it will play a negative effect on other types of innovation. This effect could be further studied with interviews as well.

CHAPTER 6 ASSOCIATION RULES AND TECHNOLOGY ADOPTION BUNDLES

This chapter reviews the different association rules that were generated from running the *apriori* algorithm. The algorithm requires a minimum threshold for the support and confidence rates. A first step consisted in gaining insight regarding the maximum number of rules that can be generated. To generate the maximum number of rules, a minimum threshold of 0 is used for both the support and the confidence measures. For each technology, this section presents the number of rules generated based on the different thresholds used to analyze the sensitivity of the association rules.

Because of the interest of this thesis in the bundles of technologies that are adopted together, the minimum support and confidence thresholds used will be dependent on the number of bundles obtained for each group of technologies. In other words, these measures can vary based on what the analysis aims to show and based on the sample of firms adopting these technologies. Because the goal is to describe technology adoption behaviours, a high confidence or a high support is not necessary. Some of these categories had a low adoption and for this reason, lower support thresholds need to be considered to find rules that represent what is happening in reality. The goal of studying this methodology is to explore how it can apply to technology adoption as it has not been in previous papers.

In the following paragraphs, each technology is referred to by its abbreviation. The full list of technologies and abbreviations were listed above in Chapter 3. For instance, in the BI section, technology ED represents Executive Dashboards for data analytics and decision-making, while BDS represents Big Data Software (e.g. Hadoop). Furthermore, rules are sorted by confidence and support respectively. Rules sorted by support are labelled as S rules (S1, S2, S3, etc.) while rules sorted by confidence are labelled as C rules (C1, C2, C3, etc.). Rules that are displayed in a graph are labelled as R rules (R1, R2, R3, etc.), which are equivalent to S rules.

6.1 Material Handling, supply chain and logistics (MHSCL) technologies

The first step in computing association rules consists in examining the descriptive statistics of the sample. These include the number of technologies adopted as well as which technologies have been adopted the most. Figure 6.1 presents the frequency plot of all the technologies adopted. The top four technologies adopted are CRM, WMS, QR and DF respectively. All of these tools had adoption rates over 35%. It is expected that the most popular rules will include at least one of these technologies. Without surprise, RFID was the least adopted technology and the only one that had less than 10% adoption rate. QR and barcodes being adopted by over 40% of firms, these companies are dependent on them, which is not helping in the adoption of RFID (Kang & Gershwin, 2005). This can be explained by the fact that firms consider QR as a legacy technology which is hard to replace, despite RFID yielding more benefits.

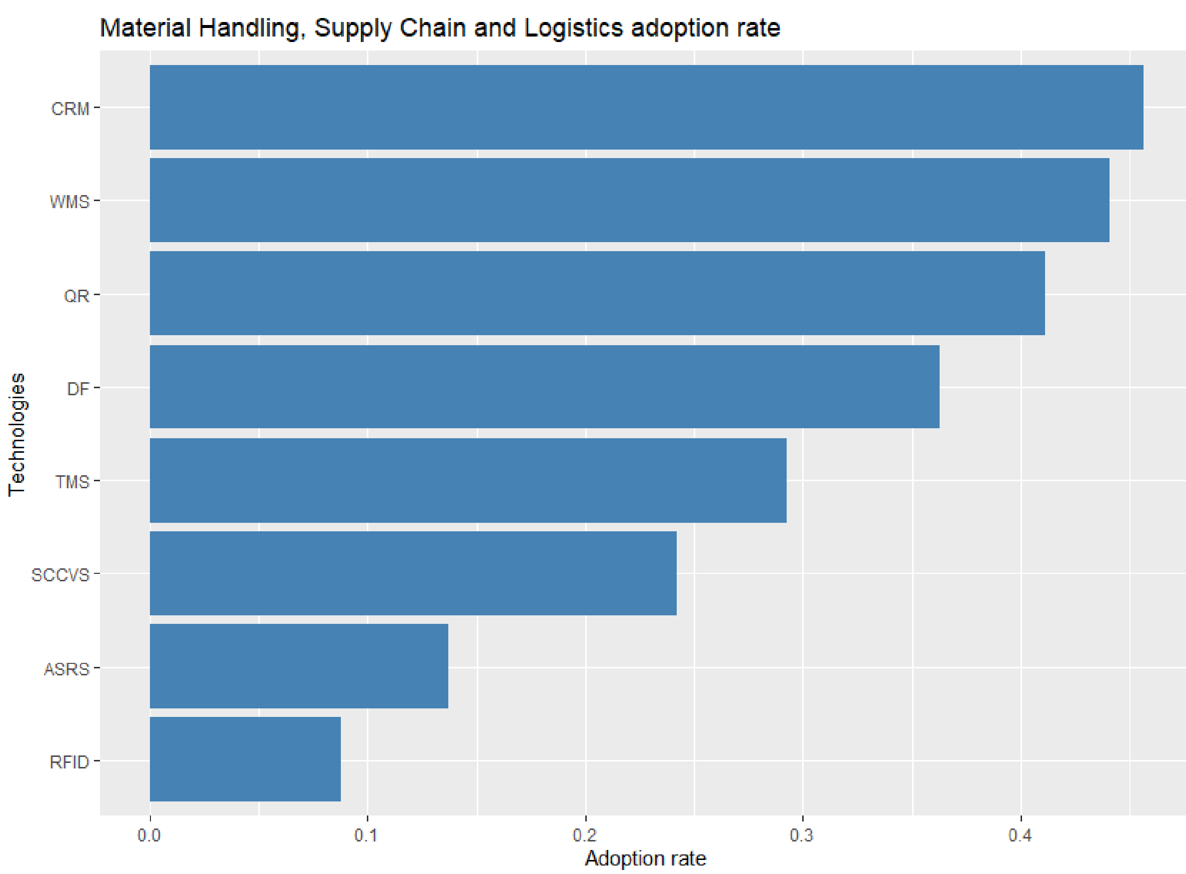

Figure 6.1: Frequency plot of material handling technologies

The reader should recall that a rule is composed of an antecedent (lhs) and a consequent (rhs). The length of a rule provides an insight into how many technologies were adopted (lhs and rhs combined). In the survey, despite the fact that MHSCL technologies are divided into eight different technologies, the maximum number of technologies adopted together is five (see Table 6.1).

Table 6.1: Material Handling technologies - Item sets length distribution

Length	**1**	**2**	**3**	**4**	**5**	**Total**
Frequency	1270	830	542	389	489	3520
Percentage	36.08%	23.58%	15.40%	11.05%	13.89%	100%

It is interesting to notice that almost 60% of MHSCL technology adopters decided to purchase one or two technologies. There are, however, 1420 firms that have adopted three or more technologies, which should highlight certain complementarities between the technologies. The next step required to compute the number of rules to find the bundles that are the most frequently adopted. Computing the maximum number of rules results in 792 rules. The maximum number of rules is actually the number of combination possibilities between the different technologies. However, as this number is too large, analyzing all the rules is very difficult. Besides their large number, the rules that have a very low confidence and support are not interesting because they can be seen as anecdotes. Consequently, an interesting rule is defined as a set of technologies that provides an advantage to a company based on the functions it can fulfil. The general scatter plot shown in Figure 6.2 gives an insight into where to look for rules. For example, there were a few very popular rules with a support greater than 0.3, which means that more than 30% of firms adopted these technologies. For these popular rules, the lift seemed close to 1 or lower than 1, which does not indicate a complementarity. In fact, a lift equal to 1 indicates that the probability of occurrence of the antecedent and the consequent are independent, thus providing an anecdotic rule. A lift lower than 1 may be interpreted as the consequent technology being a substitute of consequent technology. The dark red circles that point towards a very high lift represented bundles containing technologies that are complementary according to the algorithm and are the focus of this analysis. Only frequent item sets, for which the lift that is different than 1, are of interest for this research. Ideally, this lift needs to be higher than 1 to indicate a strong complementarity.

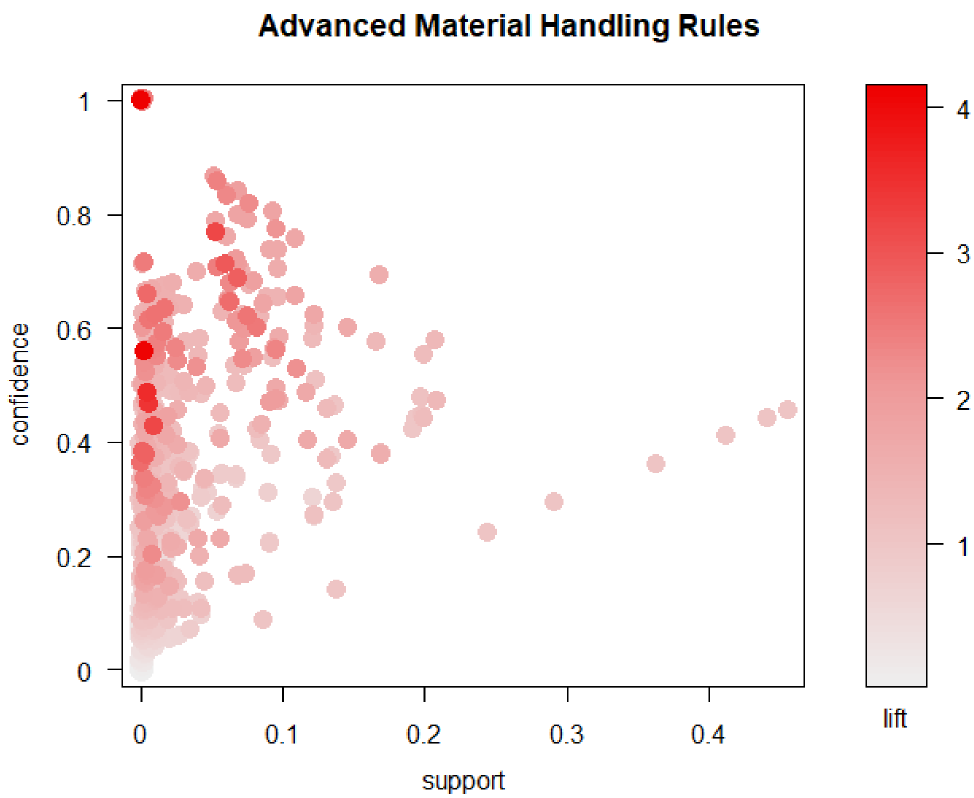

Figure 6.2: Material Handling association rules - scatter plot of all rules

Figure 6.2 highlights where the strong rules (lift > 1) are located across different confidence thresholds. To give a better idea of which thresholds were used in the final analysis, the *apriori* algorithm was run for different support and confidence thresholds. These results are shown in Table 6.2 below. The number of rules decreased much faster when the support increased to 0.1. Interestingly, when a confidence threshold of 0.8 was considered, no rules with a support greater or equal to 0.1 was found. Based on these results and to be able to capture as many rules as possible, a minimum support of 0.05 and a confidence of 0.6 was considered for this analysis into MHSCL. This enabled to observe strong rules but also frequently adopted rules.

Table 6.2: Distribution of Material Handling association rules by confidence and support

	Confidence		
Support	0.4	0.6	0.8
0.025	101	47	7
0.05	86	44	7
0.1	26	6	0

Using a minimum support of 0.05 and a minimum confidence of 0.6, 44 rules were generated, as it can be seen in Figure 6.3. The objective was to find a way to classify these rules and be able to interpret them in a practical way. An important aspect to mention is that rules are not unique set of technologies. There can be two different rules from a confidence perspective but still have the same technologies involved in the rule, which means the same support.

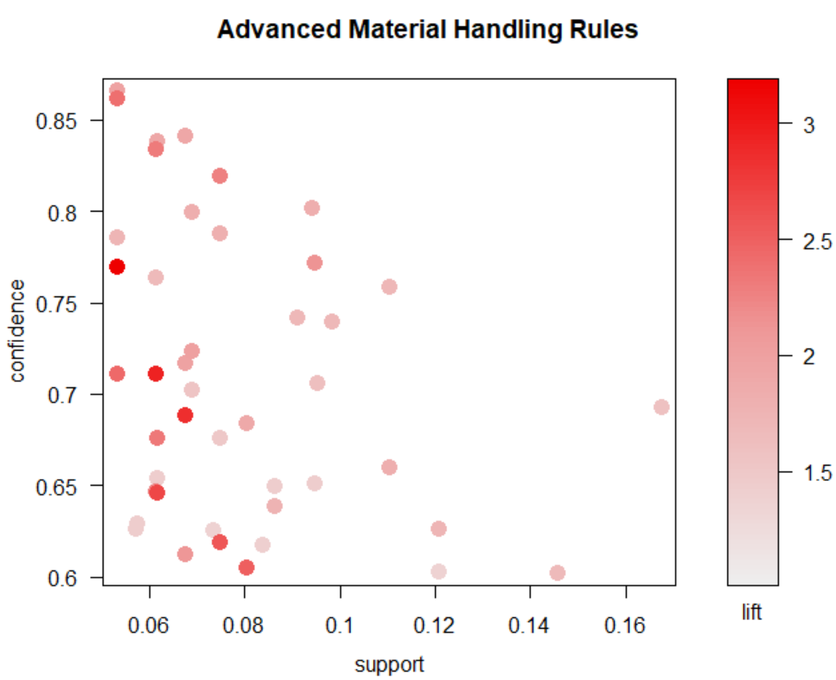

Figure 6.3: Material Handling association rules - scatter plot

To better explore these rules, they need to be sorted by confidence and by support. The results are shown in Table 6.3 and Table 6.4 respectively. The first table shows that there are seven rules with a confidence greater than 0.8. The top seven rules all have something in common: the bundles are all very similar because they involved the same technologies. In fact, the first two rules comprised the same technologies: CRM, DF, SCCVS, TMS and WMS. Consequently, both rules had the same support and a very similar confidence as well. The only measure that can be used to differentiate them is the lift. The second rule is slightly stronger in terms of complementarity between the antecedent and the consequent. However, because the lift is higher than 1 in both cases, these rules are considered similar. The support of 0.053 means that 5.3% of firms (187) adopted these technologies. In other words, the first two rules need be analyzed in the same way as items in a basket at a grocery store. Marketers found a need to predict customer behaviours in a grocery store and decided to conduct a market basket analysis. Based on this information, marketers are able to store complementary products together to maximize sales. For instance, if the relationship between milk and cereals needs to be analyzed, experts need to use the *apriori* algorithm to find association rules between these items. However, a basket can contain multiple items. A rule involves drawing one or multiple items and calculate the probability of having other items in the same basket. For instance, cereals are usually eaten with milk, which means that if cereals are drawn from a basket (rule 1: cereals → milk), there will be a high probably (a high confidence) that milk will also be in the basket. However, the other way around is different. If milk is drawn from a basket (rule 2: milk → cereals), the probability of having cereal will still remain high, but lower than the confidence of rule 1 explained above.

Table 6.3: Top 15 MHSCL association rules sorted by confidence

ID	LHS		RHS	Support	Confidence	Lift	Count
C1	{CRM, DF, SCCVS, TMS}	=>	{WMS}	0.053	0.866	1.964	187
C2	{CRM, SCCVS, TMS, WMS}	=>	{DF}	0.053	0.862	2.375	187
C3	{DF, SCCVS, TMS}	=>	{WMS}	0.068	0.841	1.907	238
C4	{CRM, SCCVS, TMS}	=>	{WMS}	0.062	0.838	1.900	217
C5	{CRM, SCCVS, TMS}	=>	{DF}	0.061	0.834	2.299	216
C6	{CRM, SCCVS, WMS}	=>	{DF}	0.075	0.819	2.258	263
C7	{SCCVS, TMS}	=>	{WMS}	0.094	0.802	1.819	332
C8	{CRM, DF, TMS}	=>	{WMS}	0.069	0.799	1.813	243
C9	{CRM, DF, SCCVS}	=>	{WMS}	0.075	0.787	1.786	263
C10	{DF, SCCVS, TMS, WMS}	=>	{CRM}	0.053	0.786	1.72	187
C11	{CRM, SCCVS}	=>	{DF}	0.095	0.771	2.126	334
C12	{CRM, DF, TMS, WMS}	=>	{SCCVS}	0.053	0.770	3.179	187
C13	{DF, SCCVS, TMS}	=>	{CRM}	0.061	0.763	1.671	216
C14	{DF, SCCVS}	=>	{WMS}	0.111	0.758	1.72	389
C15	{CRM, SCCVS}	=>	{WMS}	0.091	0.741	1.681	321

Analyzing in greater depth the first two rules suggests that the complementarity makes sense from a practical perspective. As was previously mentioned, CRM is an important tool to manage customer relationships. Because customer demand is important and can change based on factors such as seasonality or brand perception, firms may adopt a DF software to make it easier to forecast and predict the demand. A DF tool is useful in the supply management step that is directly to customer demand (see Figure 3.3). A SCCVS is necessary to integrate all supply chain actors and partners for them to have access to information from a TMS or a WMS. A SCCVS indicates collaboration and integration along the supply chain with the firm and its partners. Finally, when CRM, DF, SCCVS and TMS is adopted, it is an indication that the firm has many customers and deals with many partners, hence suggesting that the firm may be operating a large warehouse or more than one. Therefore, this would require a WMS to manage efficiently especially when all other technologies are adopted. Amongst the other rules that had slightly lower confidence levels, the same technologies were adopted, but instead of having adopted five, firms have adopted three or four of these technologies.

The bundles with fewer technologies had in general a higher support. This is expected since smaller bundles are part of the bigger ones. For example, rule C14 (DF, SCCVS, WMS) has a support of 11.1%, much higher than rule C1 (CRM, DF, SCCVS, TMS, WMS) with a support of 5.3%. Because the maximum number of technologies adopted is five, only 5.3% of firms adopted the technologies of rule C1. However, this number doubles with rule C14 because DF, SCCVS and WMS seem to be core technologies for specific firms. The adoption is obviously based on every firm's core activities. Rule C14 encompasses the companies that have adopted DF, SCCVS, WMS only, but also the firms that have adopted one or two more technologies in addition to the core three. From the 11.1% adoption rate in rule C14, 5.3% are firms that adopted the bundle in rule C1. This means that the remaining firms (5.8%) adopted either three, four or five technologies that at least contain the bundle DF, SCCVS, WMS. Despite finding high confidence rates in the rules in which companies adopt a high number of technologies, their support is usually lower. This illustrates the core technologies that are required when deciding to carry activities related to the management of the supply chain and logistics. As mentioned, the bundles with higher support have fewer technologies. This is the case when analyzing rules found in Table 6.4. For instance, rule S1 and S2 have an adoption rate of 16.8% and 14.6% respectively. Both rules have the same antecedent (SCCVS) but a different consequent (WMS and DF). These two rules highlight that when SCCVS is adopted, there is a higher chance that WMS (confidence = 69.2%) will be adopted compared to DF (confidence = 60.2%). Firms that own warehouses need a tool to manage them, but may also need to keep their inventory visible to their partners and suppliers, hence the adoption of SCCVS and WMS together. Moreover, when SCCVS and DF are adopted together, there is a 75.8% chance that WMS will be adopted (see rule S5). However, the reverse rule (S6) has a lower confidence rate (65.9%). These rules highlight the different affinities between SCCVS, DF and WMS. Taken individually, it seems that WMS has more complementarity with SCCVS, but clearly adding DF in the mix increases the chances of WMS being adopted.

In sum, the first five supply chain technologies (e.g. CRM, DF, TMS, WMS, SCCVS) seemed to be adopted together frequently, or at least different combinations of 3,4 or 5 technologies. The right bundles could be dependent of a firm's core activities, its financial capacities or many other factors.

These results highlight the many different combinations of technologies that could be adopted by firms. However, from the top 15 rules sorted by confidence, there is no mention of the other technologies such as AS/RS, QR and RFID because the minimum thresholds chosen were too high to capture these other rules.

Table 6.4: Top 15 MHSCL association rules sorted by support

ID	LHS		RHS	Support	Confidence	Lift	Count
S1	{SCCVS}	=>	{WMS}	0.168	0.692	1.571	590
S2	{SCCVS}	=>	{DF}	0.146	0.602	1.660	513
S3	{CRM, DF}	=>	{WMS}	0.121	0.603	1.367	425
S4	{CRM, WMS}	=>	{DF}	0.121	0.626	1.725	425
S5	{DF, SCCVS}	=>	{WMS}	0.111	0.758	1.720	389
S6	{SCCVS, WMS}	=>	{DF}	0.111	0.659	1.817	389
S7	{DF, TMS}	=>	{WMS}	0.098	0.739	1.677	346
S8	{DF, SCCVS}	=>	{CRM}	0.095	0.651	1.425	334
S9	{CRM, SCCVS}	=>	{DF}	0.095	0.771	2.126	334
S10	{CRM, TMS}	=>	{WMS}	0.095	0.706	1.601	336
S11	{SCCVS, TMS}	=>	{WMS}	0.094	0.802	1.819	332
S12	{CRM, SCCVS}	=>	{WMS}	0.091	0.741	1.681	321
S13	{DF, TMS}	=>	{CRM}	0.086	0.650	1.422	304
S14	{CRM, TMS}	=>	{DF}	0.086	0.639	1.760	304
S15	{DF, QR}	=>	{WMS}	0.084	0.617	1.400	295

Only in top 15 rules sorted by support in Table 6.4 does the analysis finds a rule (see Table 6.5) with QR and barcode technology: 8.4% of firms (295) adopted technologies DF, QR and WMS together.

Table 6.5: Rule that includes QR and barcode technology

ID	LHS		RHS	Support	Confidence	Lift	Count
S15	{DF, QR}	=>	{WMS}	0.084	0.617	1.400	295

From a practical standpoint, it is not the most interesting rule: the lift is lower than that of previous rules, although higher than 1. The fact that DF and QR are seen frequently together is not particularly surprising. On the other hand, if DF and QR are adopted, there is a 61.7% chance that WMS will be adopted as well. This group of technologies, especially WMS and QR are complementary because WMS requires bar coding technology to function properly. The whole point of adopting a warehouse management system is to track products and be able to move them between warehouses. QR/Bar coding technology enables the tracking of items through a WMS.

To see additional technologies appearing in the rules, one needs to lower the support to 0.025 and keep the confidence at 0.6. This does not mean that other bundles were not adopted, but that they were adopted less frequently. If the analysis had included rules that have a support between 0.025 and 0.05, the rule C23 found in Table 6.6 would not have been found as it would not make the top 15.

Table 6.6: Rule that includes ASRS technology

	LHS		RHS	Support	Confidence	Lift	Count
C23	{SCCVS, ASRS}	=>	{WMS}	0.039	0.701	1.59	136

When sorted by confidence, this rule would only be in the top 30 (ranked at number 23) that involves a technology different than the first five. This rule makes some sense from a practical standpoint because SCCVS and ASRS specifically point towards a warehouse, which would involve a WMS tool. However, this rule cannot be considered because it does not meet the minimum threshold (confidence is lower than 0.8 and support is lower than 0.05).

Finally, now that the analysis has zoomed in on a few specific rules, the next and final step consists in visualizing how these technologies are connected by drawing a network of technologies. A visual graph gives more information on the most frequently adopted technologies in bundles because it displays more than the top 15 rules. Again, the same thresholds of 0.05 and 0.6 are used for the support and confidence measures respectively.

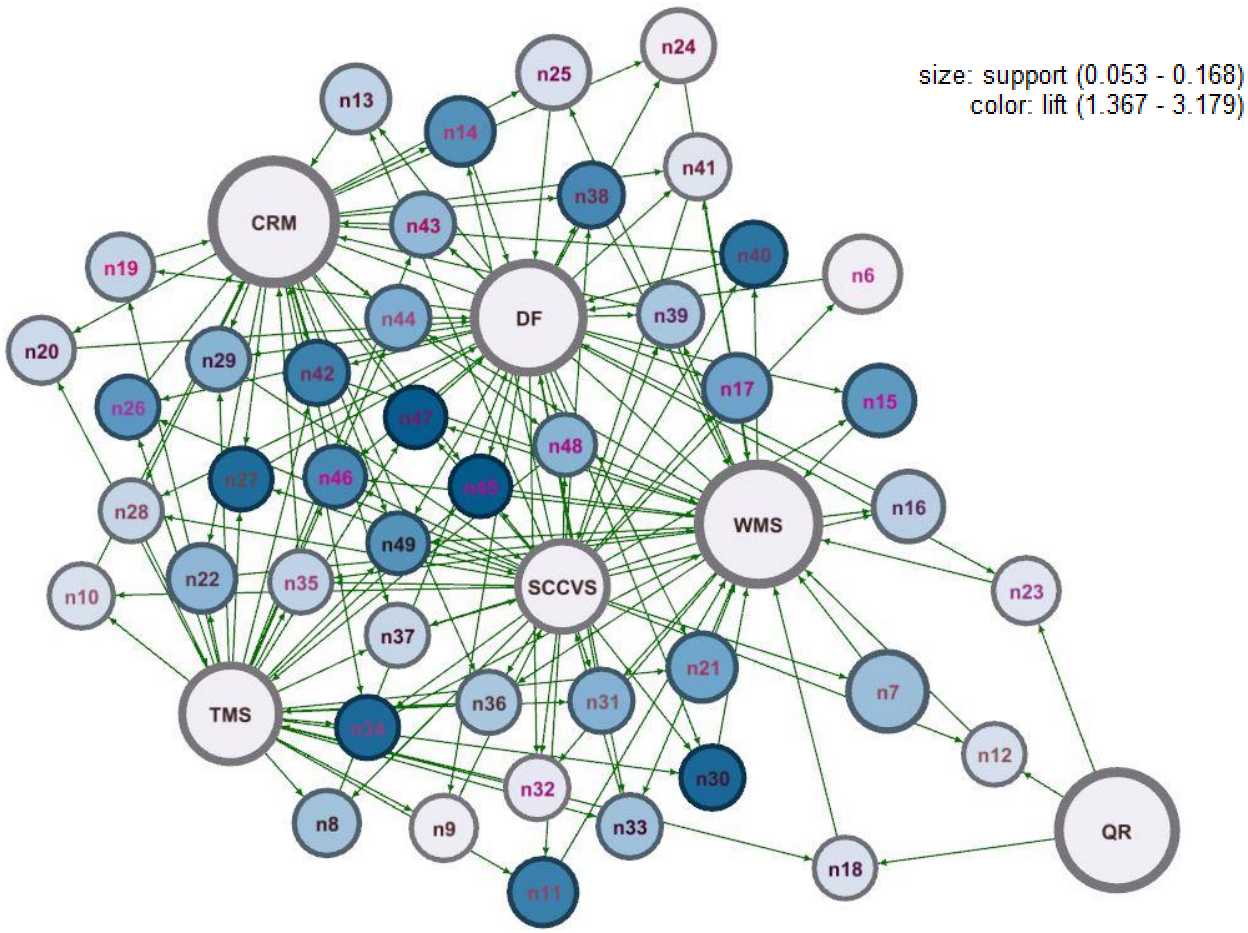

Figure 6.4: Material Handling association rules network

Figure 6.4 shows how the different material handling technologies are connected. In total, 44 rules are displayed matching the support and confidence chosen. The graph shows each technology and rules as a node. The size of each node represents the support with CRM, DF, WMS, SCCVS, TMS and QR representing the biggest nodes. Arrows pointing from the technology node to a rule node constitute the antecedent, while the consequent is comprised of an arrow from a rule towards a technology. Finally, the different shades for each node represent the confidence: the darker the shade of blue, the higher confidence this rule has.

All the lift values are greater than 1, the minimum being 1.367. The graph also shows which bundles of technologies are the most popular as represented by the size of the nodes. There are three main insights that can be extracted from Figure 6.4. First, the technologies at the centre of the network are CRM, DF, WMS, SCCVS and TMS, with DF and WMS being consequents more often than the rest. This suggests that DF and WMS would need to be bought after other technologies or that they require other technologies for firms to gain full benefits from them. Second, QR and barcode technology seems to be an isolated technology only found in small and less popular bundles. This technology is always an antecedent, which may point out that it is a technology that is generally adopted before others, i.e. products need to be identified before they can be tracked. However, Figure 6.1 showed that QR is one of the most adopted technology following CRM and WMS, which suggests that it might be a technology that is in fact less dependent on other technologies. As was previously mentioned, QR and barcodes are very useful for tracking and identifying products or materials in a warehouse. Because of the popularity of QR, firms don't seem to be adopting RFID technologies, which is what the network analysis shows. Table 6.7 is an extract from Appendix B that contains all 44 rules measured by this analysis.

Table 6.7: Rules that include QR technology

ID	**LHS**		**RHS**	**Support**	**Confidence**	**Lift**	**Count**
S15	{DF, QR}	=>	{WMS}	0.084	0.617	1.400	295
S38	{SCCVS, QR}	=>	{WMS}	0.057	0.629	1.427	202
S39	{TMS, QR}	=>	{WMS}	0.057	0.626	1.420	201

It shows the only three rules that involved QR and barcode technology. The confidence of each rule is one of the lowest amongst all the other rules explored. These rules are sorted by support and despite rule S15 being adopted by 8.4% of firms, the other two rules are less popular. However, the fact that QR is isolated from the rest of the network points towards a group of specialized firms that require this technology to conduct their operations. In the three cases shown, QR/Bar coding is adopted frequently with either a software for demand forecasting (DF), a SCCVS or a TMS. If either of these two technologies are present, it leads about 60% of firms to adopting a WMS.

From a practical perspective, these results allow to draw a few conclusions. The most popular rules involve the same five technologies regardless of them being sorted by support of confidence. The five technologies are the following: CRM, DF, TMS, WMS, SCCVS. The other technologies (ASRS, QR, RFID) are more independent of the top five and will be adopted on a case-by-case basis. For instance, companies that have large warehouses might require ASRS technology but it is not a necessity. Firms might be using other means to retrieve their parts or items such as robots that will be discussed in a later section. Moreover, the sample of firms using MHSCL technologies appears to be heterogenous, which has already been discussed in the regression analysis.

QR adoption is widespread but may be adopted in specific scenarios which makes it part of bundles that are outside the fixed thresholds. On the other hand, RFID was not widely adopted, at least not at the time of the survey. A low adoption of RFID was expected because of the popularity of barcodes. According to Kang and Gershwin (2005), firms are too dependent on barcode and are not yet comfortable to upgrade to RFID. Furthermore, the upgrade to RFID would require more IT investments due to the large amount of data that will be generated (Attaran, 2007). All this data would need to be collected and stored to be potentially analyzed.

6.2 Business Intelligence technologies

In contrast with the MHSCL category, Business Intelligence (BI) has only five technologies to choose from. Consequently, there are fewer possible combinations of technologies, and thus that the support for the bundles will be higher. The first step, however, is to examine at the frequency of adoption of each technology taken individually (see Figure 6.5). The top three most adopted technologies are SaaS, also known as cloud computing software, ED for decision-making, and RTM. Nowadays most companies need some form of analytics to guide decision-making. SaaS is also very popular because it allows the use of software from anywhere in the world in a browser, without the need for any installation or maintenance team. Perhaps the most striking result is the fact that BDS was by far the least adopted out of the five BI technologies (under 25% adoption rate). All the other technologies exhibited over 30% adoption rate, with SaaS and ED being over 50%. These results were expected from a practical standpoint because SaaS contributes to lower costs in adopting any kind of software whereas ED is an important technology to allow high-level analytics to be displayed for executives.

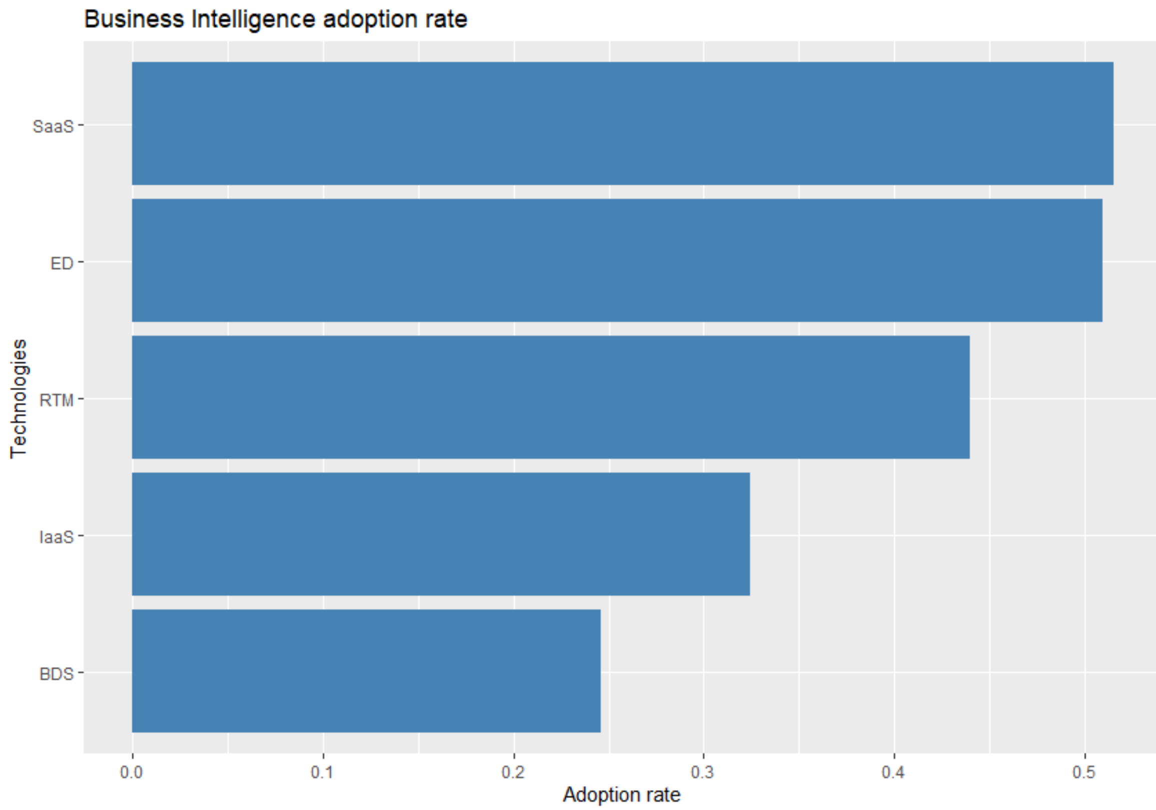

Figure 6.5: Frequency plot of business intelligence technologies

Because there are very few technologies, similar types of complementarities are expected to be found. To explore which technologies are adopted together, the association rules need to be computed using the *apriori* algorithm. From the summary of frequent item sets in Table 6.8, less than 13% of firms have adopted more than three technologies with the majority having adopted only one or two. As was previously mentioned, BI technologies can be quite expensive and have a recurrent cost, which can explain why very few companies adopted more than three technologies. Besides the obvious ED or SaaS choices that are crucial data elements to consider, companies may prefer to adopt technologies in the other families that are more specific to their core business activities.

Table 6.8: Business intelligence technologies - Item sets length distribution

Length	1	2	3	4	5	Total
Frequency	1045	724	394	174	130	2467
Percentage	42.36%	29.35%	15.97%	7.05%	5.27%	100%

Using a minimum support and confidence thresholds of 0, the maximum number of possible association rules is 80. Figure 6.6 shows a scatter plot of all 80 possible rules. There are some very popular rules with more than 50% adoption, but their lift seems to be very low. Based on this graph, a minimum support of 0.5 and minimum confidence of 0.5 are fixed, allowing the algorithm to capture the two rules that have a support level that is greater than 50%. Rules with a support close the minimum threshold have a confidence higher than 80%. The rules of interest are highlighted in a blue rectangle in Figure 6.6.

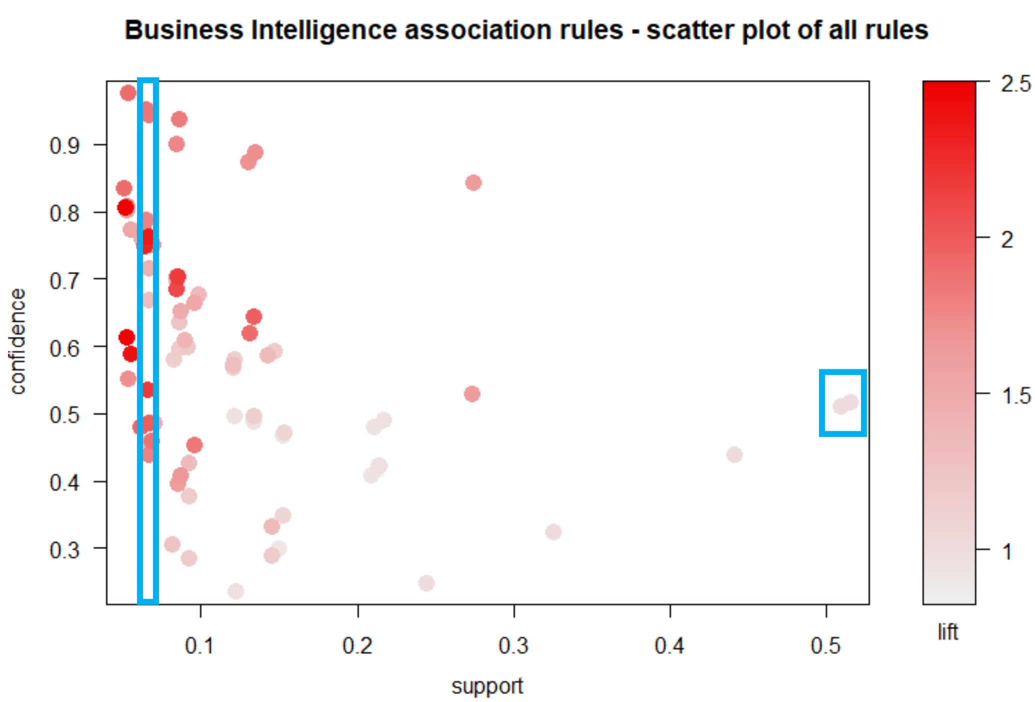

Figure 6.6: Business intelligence association rules – scatter plot of all rules

Table 6.9 highlights information about the number of association rules when the algorithm is run for different support and confidence thresholds. Unlike MHSCL technologies, it appears that BI technologies generated more rules even though they have been less adopted in general. For example, there are three rules with a minimum support of 0.1 and a minimum confidence of 0.8. Based on this table, the same thresholds chosen with material handling technologies (i.e. S=0.025, C=0.6) could be used to capture as many rules as possible. However, Table 6.9 highlights that there is no change in the number of rules generated between a support of 0.025 and 0.05. Figure 6.6 illustrated that there are two rules with a high support level, but with a confidence threshold between 0.5 and 0.6. For these reasons, a different threshold for these technologies is used: S=0.05 and C=0.5 with the goal of getting a good number of rules to analyze.

Table 6.9: Distribution of Material Handling association rules by confidence and support

	Confidence		
Support	0.4	0.6	0.8
0.025	69	35	12
0.05	69	35	12
0.1	25	5	3

The *apriori* algorithm generates 48 rules when using a minimum support of 0.05 and a minimum confidence of 0.5. The results for the top 15 rules sorted by confidence are shown in Table 6.10. The top eight rules are interesting because they all point towards SaaS technology as the consequent, hence justifying the fact that SaaS has a high adoption rate. All the top eight rules have a confidence higher than 0.8 and a lift higher than 1. In other words, if the top 8 antecedent bundles displayed in Table 6.10 are adopted, there is a very high chance (greater than 80%) that SaaS is also adopted. Moreover, it is logical to believe that many BI technologies may also be adopted as a cloud computing software, which can explain why SaaS is always a consequent. Interestingly, all the antecedents of the first eight rules contain IaaS, which represents cloud computing hardware. Therefore, if a firm has adopted the hardware for cloud computing, there is a high chance that it will also have adopted cloud computing software. There are two possible explanations for this behaviour. Either these adopters are companies that want to sell cloud computing software or some of these firms want to keep their data and applications within their own facilities but make it accessible to their employees anywhere in the world from a browser.

Table 6.10: Business Intelligence top 15 association rules sorted by confidence

ID	LHS		RHS	Support	Confidence	Lift	Count
C1	{BDS, ED, IaaS, RTM}	=>	{SaaS}	0.053	0.977	1.897	130
C2	{BDS, ED, IaaS}	=>	{SaaS}	0.063	0.951	1.846	156
C3	{BDS, IaaS, RTM}	=>	{SaaS}	0.066	0.942	1.828	162
C4	{ED, IaaS, RTM}	=>	{SaaS}	0.086	0.938	1.821	212
C5	{BDS, IaaS}	=>	{SaaS}	0.084	0.900	1.746	206
C6	{IaaS, RTM}	=>	{SaaS}	0.135	0.886	1.719	333
C7	{ED, IaaS}	=>	{SaaS}	0.133	0.877	1.702	327
C8	{IaaS}	=>	{SaaS}	0.273	0.841	1.633	674
C9	{BDS, ED, IaaS, SaaS}	=>	{RTM}	0.053	0.833	1.895	130
C10	{BDS, ED, IaaS}	=>	{RTM}	0.054	0.811	1.844	133
C11	{BDS, ED, RTM, SaaS}	=>	{IaaS}	0.053	0.807	2.487	130
C12	{BDS, IaaS, RTM, SaaS}	=>	{ED}	0.053	0.802	1.575	130
C13	{BDS, IaaS, SaaS}	=>	{RTM}	0.066	0.786	1.788	162
C14	{BDS, IaaS, RTM}	=>	{ED}	0.054	0.773	1.518	133
C15	{BDS, ED, SaaS}	=>	{RTM}	0.065	0.770	1.752	161

These results suggest that BI technologies started to reach their maturity level in 2014, at the time of the survey. Although not every firm adopted them, it seems like many of the possible bundles have been adopted. In total, there are 26 total bundles that could have been adopted (excluding the combinations of only 1 technology) from which six of them contain four or five technologies. All bundles of four or five technologies are in the top 15 of rules sorted by confidence. From the previous rules, all lifts were higher than 1, hence why all the rules can be considered pertinent because there is a dependence between the consequents and antecedents. Analyzing the results from the support perspective provides insight into which bundles are the most popular. Table 6.11 highlights these same rules sorted by support.

Table 6.11: Business Intelligence top 15 association rules sorted by support

	LHS		RHS	Support	Confidence	Lift	Count
S1	{}	=>	{SaaS}	0.515	0.515	1.00	1271
S2	{}	=>	{ED}	0.510	0.510	1.00	1257
S3	{IaaS}	=>	{SaaS}	0.273	0.841	1.633	674
S4	{SaaS}	=>	{IaaS}	0.273	0.530	1.633	674
S5	{BDS}	=>	{ED}	0.146	0.593	1.164	360
S6	{BDS}	=>	{RTM}	0.144	0.586	1.334	356
S7	{IaaS, RTM}	=>	{SaaS}	0.135	0.886	1.719	333
S8	{RTM, SaaS}	=>	{IaaS}	0.135	0.640	1.972	333
S9	{ED, IaaS}	=>	{SaaS}	0.133	0.877	1.702	327
S10	{ED, SaaS}	=>	{IaaS}	0.133	0.618	1.904	327
S11	{ED, RTM}	=>	{SaaS}	0.122	0.566	1.098	301
S12	{RTM, SaaS}	=>	{ED}	0.122	0.579	1.136	301
S13	{ED, SaaS}	=>	{RTM}	0.122	0.569	1.294	301
S14	{BDS, RTM}	=>	{ED}	0.097	0.674	1.323	240
S15	{BDS, ED}	=>	{RTM}	0.097	0.667	1.516	240

In the top 15 rules shown in Table 6.11, the first two rules are different (S1 and S2). The antecedent is empty, which means that if a company did not adopt any technology, it has a good chance (51%) of adopting ED or SaaS. The 51% also corresponds to the number of companies that have adopted these technologies. It does not mean that other technologies were not adopted but rather that these two technologies are very popular. This information was already known, however, because of the frequency plot in Figure 6.5. This rule may potentially indicate that if firms were to adopt a single technology there is a high chance that it will be SaaS or ED. However, the lift is equal to 1, which indicates that the antecedent and the consequent are independent. The rule is less useful for predicting the consequent when the lift is equal to 1. Rules S3 and S4 are identical. Because they involve the same technologies (SaaS and IaaS), they have the same support, in addition to both lifts being higher than 1. The lift value indicates that both technologies increased the likeliness of the other one being adopted by the same percentage (lift of 1.633 = 63.3% increase). However, the main difference lies in the confidence measure. Rule S3 has a higher confidence rate than rule S4. This suggests that if IaaS has been adopted, there was an 84% chance that SaaS was adopted. The reverse rule only had a 53% confidence of IaaS adoption if SaaS was adopted. This rule was previously discussed when analyzing the top 15 rules sorted by confidence (rule C8). If a company adopted IaaS, it had a good chance of adopting SaaS. Adopting IaaS has a direct relationship with SaaS because cloud computing software needs some form of hardware to function. Normally, firms are more reluctant to save their data in a cloud that is hosted by other companies. Moreover, firms that have adopted IaaS will not have any problems adopting SaaS because they have already made the business decision of putting their data in the cloud. However, a firm that adopted SaaS might be more reluctant to adopt IaaS as they prefer to keep their data private. In fact, SaaS only grants the ability to save data that is used with the specific software adopted, but IaaS can be considered as an external hard disk (in the cloud). A few common examples of IaaS include Dropbox, One Drive and Google Drive. There are definitely fewer companies who are willing to use these services. Furthermore, it should be noted that while the rules by confidence showed all the possible combinations of 4 and 5 technologies, the rules sorted by support highlight many different bundles of 2 and 3 technologies, which are the most frequently adopted. The main problem, faced by firms when adopting technologies, is having an IT team to support it. With SaaS, this is no longer needed, which justifies its high adoption rate. Moreover, it is not surprising to see ED highly adopted as well. In addition to not having an IT team, companies may prefer to save costs on data analytics by using an executive dashboard (ED). Using a data warehouse to collect data and try to analyze afterwards can be costly because a firm has to depend on technical employees to collect and consolidate the data to be analyzed by using a process of Extraction, Transformation and Loading (ETL) (Kroenke & Auer, 2012). The use of a single dashboard (via an ED adoption) will allow to consolidate the data in a single screen, making analysis and decision-making easier without having to depend on IT specialists (Price, 2006). However, it should be noted that while Excel sheets can be used to store simple data and then linked back to an ED, most firms will have a lot of data that requires a data warehouse or a BDS. This is why there are many rules that have BDS and ED combined (e.g. C2, C9, C10, S5). In particular, rule S5 has a low confidence (below 60%), because

BDS is required to implement artificial intelligence (AI). Particular rules with BDS will be discussed below.

The last step of this analysis consists in mapping the network of connected technologies. As opposed to the MHSCL category that had only five out of eight technologies adopted, the rules found with the BI category involved all five technologies. The network in Figure 6.7 shows the top 48 most frequently adopted rules. The two biggest nodes correspond to the first two rules (R1 and R2 on the graph) sorted by support which represent the adoption of technologies SaaS and ED respectively. Furthermore, all the different technologies are interconnected in the centre. As was previously mentioned, all the technologies in the BI category have been adopted and because firms are using a great number of these technologies at the same time, the network is very homogenous. Unlike what the results obtained with the MHSCL category, there is no isolated technology in this network. Despite being the less adopted technology, BDS is still at the centre of some important rules that grants insights into how important this technology can be. First, BDS is always an antecedent. This is logical from a practical standpoint because more often than not, ED and RTM or any other kind of data visualization tool will require some form of big data software or at least relational databases. For example, analyzing R5 and R6 on the graph, neither rule has the highest of confidences (because the nodes are light-coloured). Table 6.11 shows that their confidence rate is 0.59, which means that if BDS is adopted, there is a 59% chance that either ED or RTM are adopted. However, ED is adopted in many more scenarios. As was previously mentioned, BDS is an important asset to be able to effectively adopt AI, especially in large firms or those with a lot of data. Due to the low adoption rate at the time of the survey, it may be predicting a low adoption rate of AI in the future. While it is not required for smaller companies that may have enough data from their operational software (e.g. ERP or CRM), the low adoption of BDS could be one of the reasons why AI adoption is not high in Canada. Many companies are still using relational databases (RDB) to power their dashboards and data analysis. RDB may allow some form machine-learning use cases for enterprises with less data capabilities. Because AI is becoming more widespread, firms have to transform the way they manage their business and customers because of the amount of data that is available in today's world (Tambe, 2014). This data-driven revolution is a result of new data sources that include social media, consumer preferences expressed on the web and on mobile phones, and RFID (Thomas Davenport, 2014). From the previous analysis on MHSCL technologies, it was mentioned that RFID is not yet widely adopted, which can result in a slow AI adoption in certain industries. Despite its low adoption rate at the time of the survey, there are many benefits of adopting a BDS (e.g. Hadoop) that have been highlighted in the literature that can result in cost reductions and faster decision-making that can improve products and services offered to customers (Thomas Davenport, 2014). For smaller firms, a BDS remains something to keep in mind if their volume of data collected beings to grow.

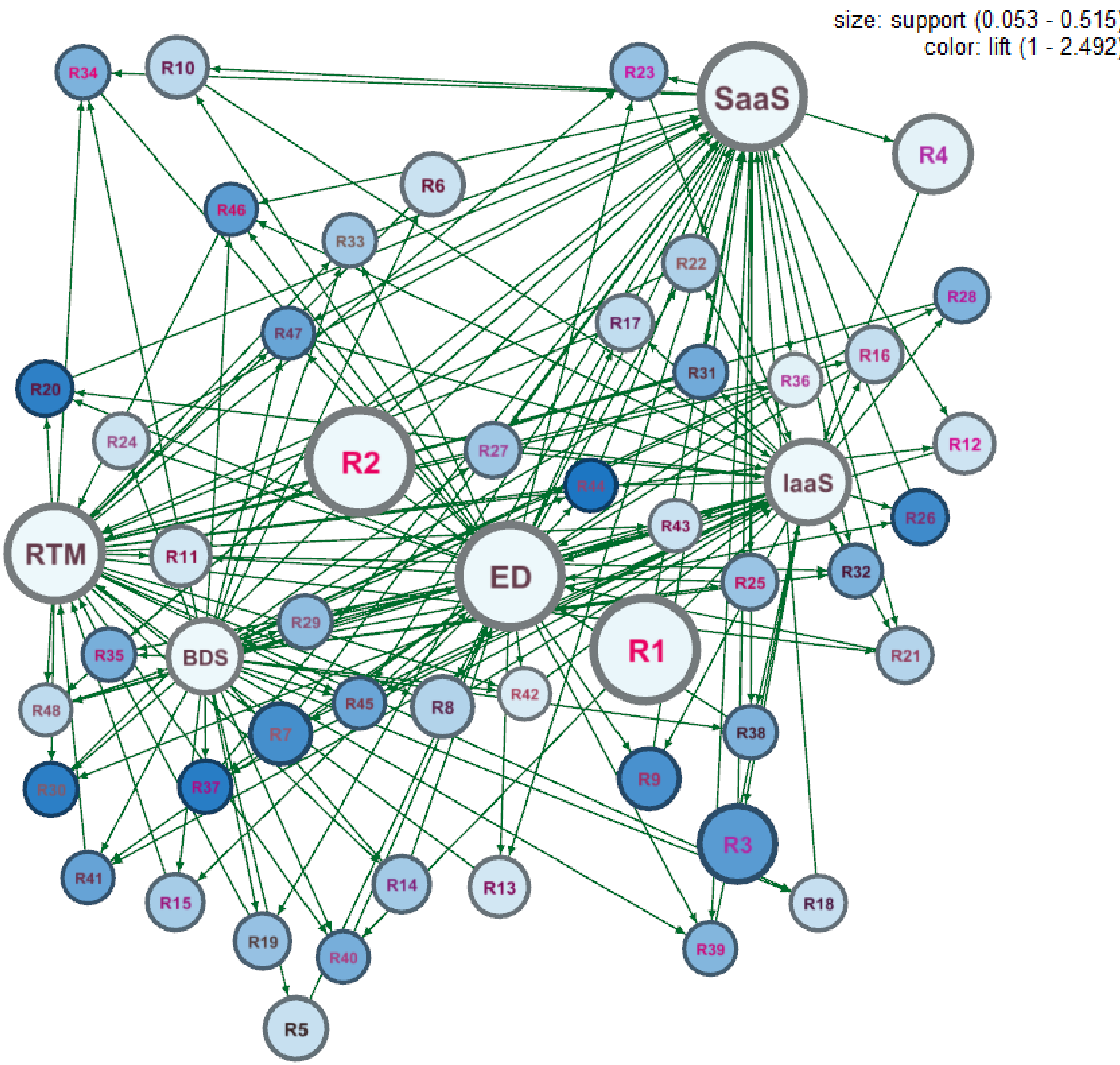

Figure 6.7: Business Intelligence association rules network

6.2.1 Descriptive statistics

While association rules can give valuable information related to the best practices in technology adoption, it is important to also explore the most frequently adopted bundles and compare them with general firm factors (e.g. industry, size and age of a firm). Figure 6.8 shows the different technology bundles adopted by firms. As opposed to what association rules yield, the data only included firms that have adopted exclusively the technologies in the bundle. For instance, BDS, SaaS, IaaS represented firms that only adopted these three technologies. It should also be noted that the bundles displayed represented a total of 76% of firms having adopted at least one BI technology. Unsurprisingly, many firms only adopted SaaS or ED, which is what was anticipated to be found since SaaS adoption is cheaper for firms, especially the smaller ones that do not have capital to adopt expensive technologies. On the other hand, ED is a must for analyzing high-level data of the firm.

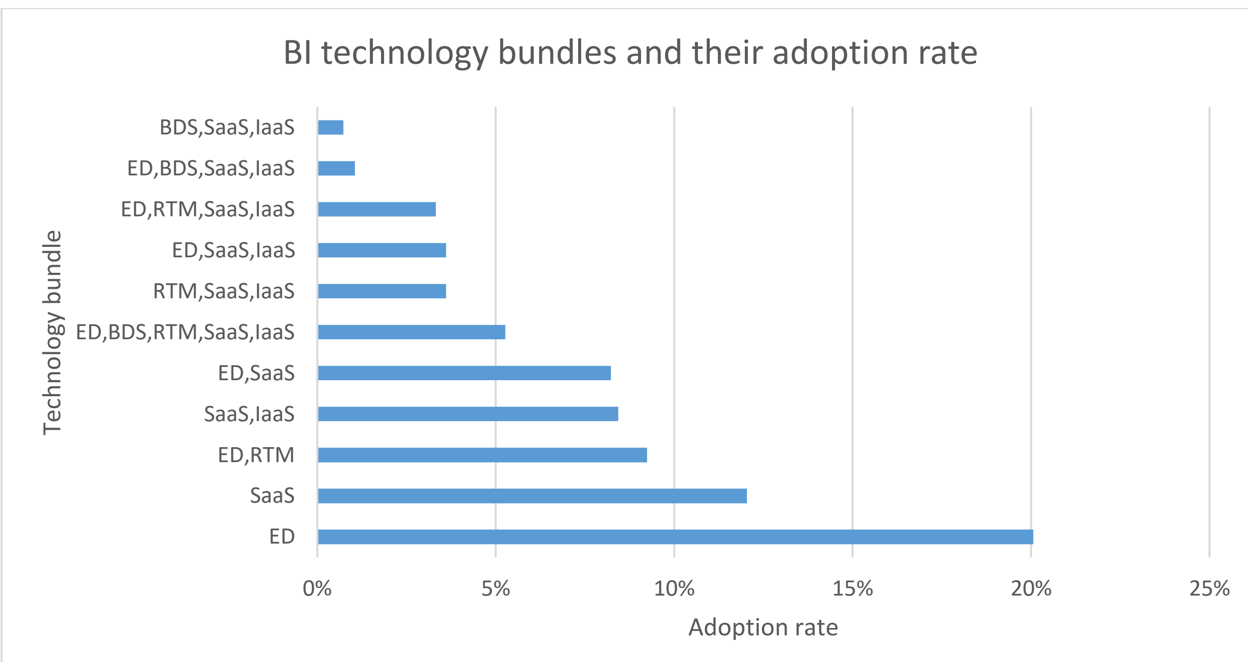

Figure 6.8: Most frequently adopted BI technology bundles (exclusive technologies)

Table 6.12 shows the results regarding the different BI bundles adopted by age, size and revenue of the firm. Analyzing these results, smaller firms in general prefer to adopt SaaS or IaaS (B11 and B12). In fact, the mean size of those who adopted SaaS only is 71.05 employees, which can be explained by the fact that smaller firms can save costs by adopting it. For SaaS and IaaS combined (B12), firms are even smaller with an average number of employees of 41.05. As was previously mentioned, IaaS can also be a source of cost reduction as firms who do not have hardware and storage capacity can buy them in the cloud. These services can include Dropbox or Google Drive which can be widely used by smaller firms that don't have an IT department. The other interesting finding is regarding ED technology. Firms who adopted it had more employees in general compared to firms having adopted SaaS and IaaS. B2 has mean size of 89.43, which is higher than the bundles containing SaaS or IaaS only. This can be noticed in B8 as well. B12 has a mean size or 41.05. When ED was added in the mix (see B8), the mean size increased to 219.35. This result was expected as ED is a tool that is mostly used for executives. Smaller firms will tend to use a simple tool such as Excel to power their dashboards. Larger firms might prefer a more powerful tool such as Tableau or Power BI to build their dashboards allowing them to monitor their company's main key performance indicators (KPI).

Table 6.12: BI technology adoption by age, revenue and size

ID	Bundles of technology	Age	Revenue	Size	N
B1	BDS, SaaS, IaaS	17.51	186M	147.76	18
B2	ED	15.84	46M	89.43	495
B3	ED, BDS, RTM, SaaS, IaaS	16.75	128M	175.23	130
B4	ED, BDS, SaaS, IaaS	15.86	57M	81.78	26
B5	ED, RTM	11.58	60M	124.65	228
B6	ED, RTM, SaaS, IaaS	13.66	213M	226.63	82
B7	ED, SaaS	17.53	316M	377.81	203
B8	ED, SaaS, IaaS	13.04	95M	219.35	89
B9	Other	17.49	15M	33.76	5580
B10	RTM, SaaS, IaaS	15.75	58M	53.10	89
B11	SaaS	16.31	39M	71.05	297
B12	SaaS, IaaS	16.55	29M	41.05	208

There is no general finding about the age of the firm. It varied between an average of 11.58 and 17.53. In terms of revenue, it appears that firms that had a higher revenue adopted four or five technologies. For instance, all firms that have adopted bundles with four or five technologies have a revenue higher than 100 million dollars, while other firms are between 10 and 30 million. This was expected and should be similar for all families of technologies. The regressions that were presented above showed that CAPEX was a good instrument to predict the number of adopted technologies (the coefficient was positive and significant). The only exception is for bundles B3 and B7. B3 contained five technologies but an average revenue of 57M, which is below 100M. It should be noted that there were only 26 firms that adopted B3, with an average number of employees of 81.78, so the lower revenue could be driven their size. On the other hand, B7 only showed two technologies but these firms have an average number of employees of 377.81, which could be what is driving their higher revenue.

Obviously, firms were not only adopting BI technologies. The average number of technologies adopted from the other categories in shown in Figure 6.9. PF technologies were less popular overall, but this was probably not depending on BI technologies. In fact, PF is the category that was the less frequently adopted. MHSCL and DIC technologies were widely adopted as the average number of technologies adopted was roughly between 1 and 3.5 for each category. Analyzing the bundles made of four or five BI technologies, there was an average of two MHSCL and three DIC technologies adopted.

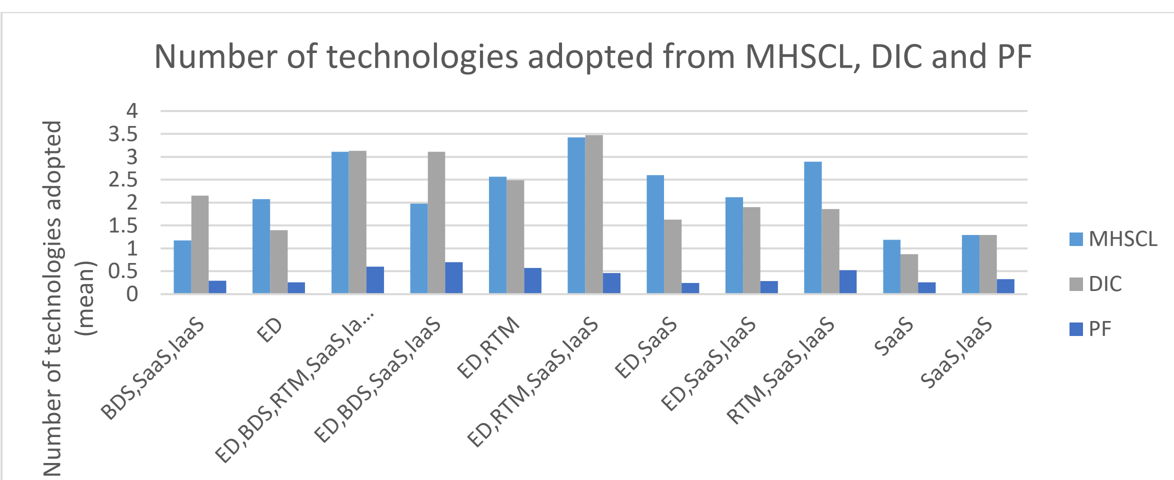

Figure 6.9: Other technologies adopted by firms using BI technologies

Finally, the type of innovation introduced by firms adopting these bundles can be seen in Figure 6.10. In general, 80% of firms that adopted these BI technologies are introducing some form of innovation. However, there are two bundles that are closer to 60% of propensity to innovate: SaaS and {SaaS, IaaS}. This could be the case because both of these technologies provide software accessible from a browser. It can reduce costs for smaller firms but does necessarily stimulate innovation. On the other hand, tools such as ED, BDS or RTM should increase the propensity to innovate because they bring data that can be used to introduce process improvements. A similar result was found in the regressions that were presented above: the higher the number of advanced technologies adopted, the higher the propensity to innovate. While the study did not focus on single technologies, it was expected that these technologies, in particular, played an important role.

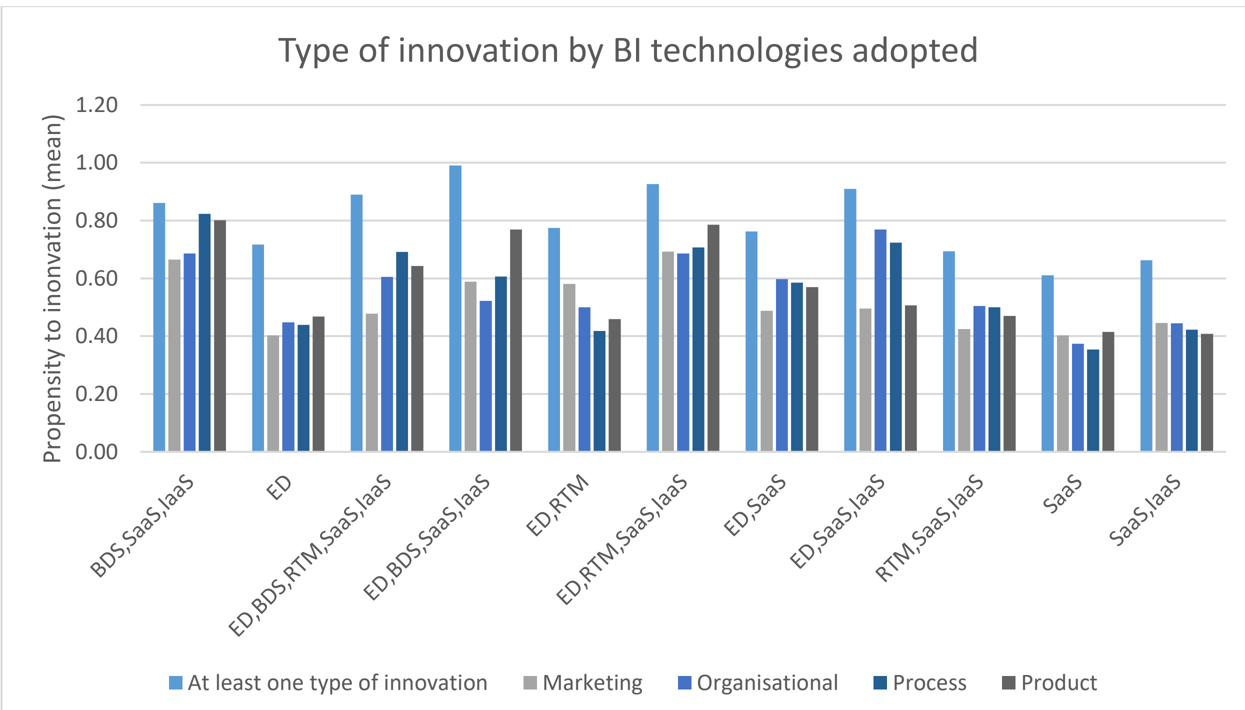

Figure 6.10: Type of innovation by bundles of BI technologies adopted

6.3 Design and information control

Design and Information Control (DIC) technologies are different than the first two categories because they have twelve different technologies. The expectation was to have a lot of different bundles of technologies adopted. Figure 6.11 shows the count of each technology being adopted. The top four technologies have all been adopted by more than 35% of the companies (which represented more than 1000 firms). However, this adoption rate dropped significantly for the rest of technologies. Unsurprisingly, EDI was one the most adopted technologies with more than 50% of firms using it.

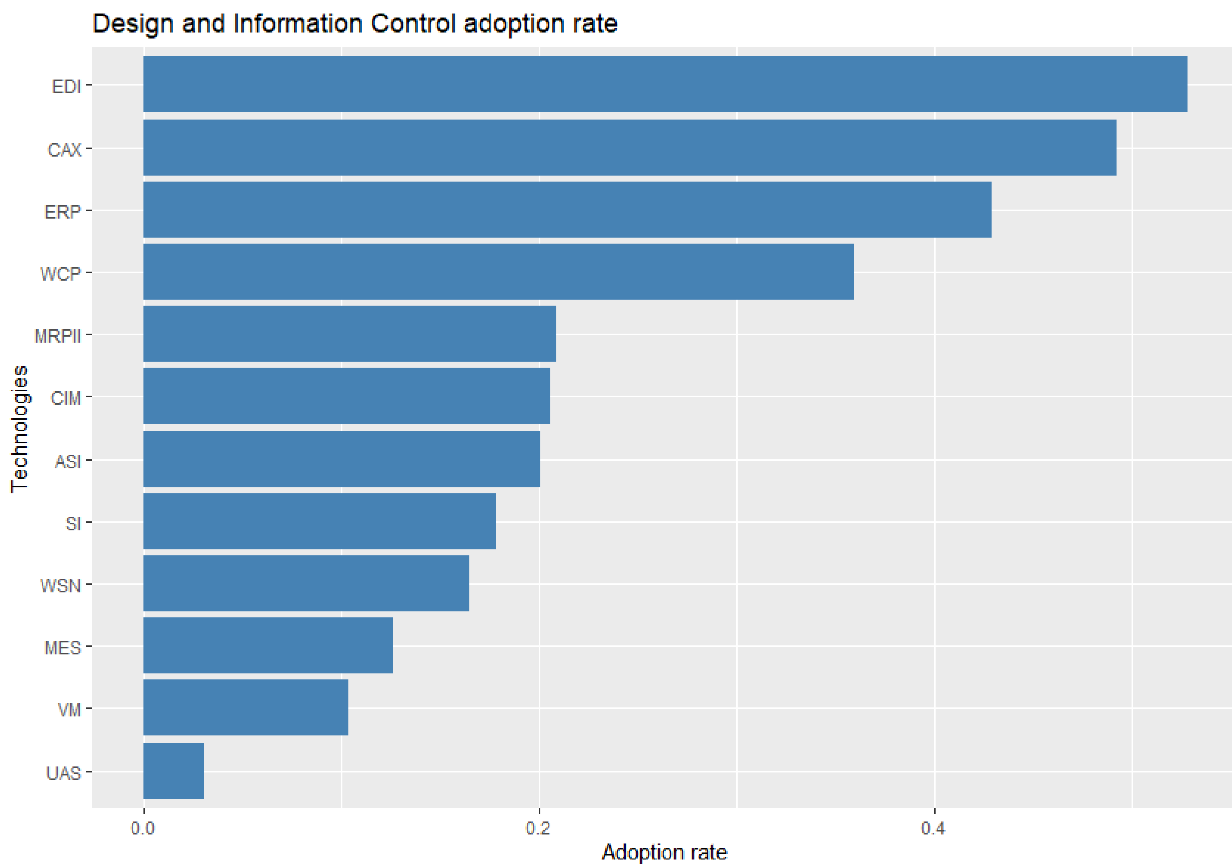

Figure 6.11: Frequency plot of Design and Information Control technologies

From the 3817 firms that adopted DIC technologies, almost 70% adopted three or fewer technologies while only 5.21% adopted eight or more technologies (see Table 6.13). There are more firms who adopted DIC technologies compared to BI and MHSCL. This could be a reason why firms have adopted fewer BI technologies in general. In fact, companies might have prioritized technologies that could help them run their core business activities (i.e. MHSCL or DIC in this case), which leaves less capital to invest in BI technologies. In the case of AMT adoption specifically, the recent contribution of Moeuf, Pellerin, Lamouri, Tamayo-Giraldo, and Barbaray (2018) showed that cost is an important factor and the advantages of adopting such technologies are still not demonstrated. The high capital investment required for these technologies can explain why more than 50% of firms have only adopted one or two technologies.

Table 6.13: Design and Information Control technologies - Item sets length distribution

Length	Frequency	Percentage
1	1222	32.01%
2	885	23.19%
3	482	12.63%
4	367	9.61%
5	259	6.79%
6	237	6.21%
7	166	4.35%
8	97	2.54%
9	51	1.34%
10	36	0.94%
12	15	0.39%
Total	3817	100%

In total, there are 24432 possible rules that can be found by having a support and confidence thresholds of 0. Figure 6.12 shows the 24432 rules in a scatter plot. Analyzing the plot, there seems to be a great number of rules with a confidence of 1. Some of them even have a high lift (circles in bold red indicate a high lift value). However, their support seems to be very low. It is expected to find that some specialized firms are adopting a specific set of technologies. There were a few rules with a support higher than 0.4 but the confidence is below 0.5. By analyzing Figure 6.12, it is certain that the *aprori* algorithm needs to be run with different thresholds of support and confidence to find and explain interesting rules. The goal is to find rules with the highest possible confidence and support values.

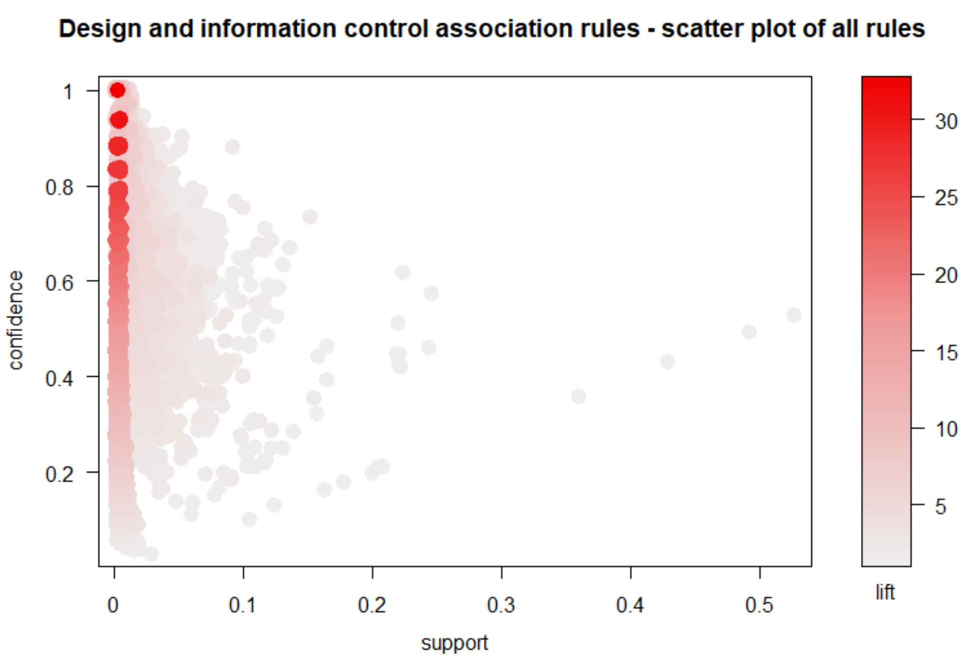

Figure 6.12: Design and Information Control association rules – scatter plot of all rules

Table 6.14 shows the distribution of rules by changing the support and the confidence. There are a lot of rules generated using a confidence of 0.6 and a support of 0.05 like it was used for other categories. To have a lower number of rules to analyze, a support of 0.05 was used and the confidence level was increased to 0.7 (from 0.6). In both cases, the rules that had a confidence of 1 were not being generated, which required the algorithm to be computed a second time with no minimum support threshold and a confidence of 1.

Table 6.14: Distribution of Design and Information Control association rules by confidence and support

	Confidence		
Support	**0.4**	**0.6**	**0.8**
0.025	1442	851	76
0.05	298	141	3
0.1	39	11	0

When running the algorithm with a confidence of 0.7 and a support of 0.05, there are 57 rules generated (down from 141 with a confidence of 0.6). These rules were sorted by confidence (see Table 6.15) and support (see Table 6.16). Only the top 15 rules are displayed. The first seven rules involve the same technologies as consequents: CAX (i.e virtual product development including CAD, CAE and CAM) and ERP. These rules also contain a variety of other technologies as antecedents including MES, MRP II, EDI and SI. The first three rules showed a complementarity between certain technologies. For instance, CAX and VM were both pointing towards a virtual way of working, whether it’s about product development or manufacturing. EDI can be seen as a facilitator to virtual manufacturing because it allows for files to be shared internally with different teams or externally with partners. However, it can be argued that EDI is used by so many companies since it was the most adopted technology (see Figure 6.11). It is also worth noting that EDI is not only specific to manufacturing. Most companies would have adopted it because it grants the ability to share files and other types of information very easily.

Table 6.15: Design and Information Control top 15 association rules sorted by confidence

	LHS		RHS	Support	Confidence	Lift	Count
C1	{ERP, VM}	=>	{CAX}	0.053	0.899	1.824	204
C2	{VM}	=>	{CAX}	0.091	0.884	1.793	349
C3	{EDI, VM}	=>	{CAX}	0.052	0.883	1.793	197
C4	{CAX, EDI, MRPII}	=>	{ERP}	0.061	0.797	1.857	232
C5	{MRPII, SI}	=>	{ERP}	0.067	0.789	1.837	254
C6	{MES, SI}	=>	{ERP}	0.051	0.783	1.824	195
C7	{MES, MRPII}	=>	{ERP}	0.059	0.782	1.821	226
C8	{CIM, WSN}	=>	{WCP}	0.064	0.766	2.128	245
C9	{CAX, MRPII}	=>	{ERP}	0.095	0.766	1.785	361
C10	{MRPII, WSN}	=>	{ERP}	0.055	0.760	1.770	209
C11	{MRPII, WSN}	=>	{EDI}	0.055	0.760	1.438	209
C12	{ERP, WCP, WSN}	=>	{EDI}	0.056	0.760	1.438	215
C13	{EDI, MRPII}	=>	{ERP}	0.099	0.749	1.743	378
C14	{EDI, ERP, WSN}	=>	{WCP}	0.056	0.749	2.083	215
C15	{ERP, SI, WCP}	=>	{EDI}	0.054	0.749	1.418	206

As seen with other technologies, the confidence decreases by a good margin when the focus is shifted to the most frequently adopted bundles of technologies. However, in this case, the minimum confidence threshold is still at 0.7 (see Table 6.16). The most popular bundle is rule S1 (e.g. MRP II and ERP), which represent respectively Manufacturing Resources Planning (MRP II) and Enterprise Resource Planning (ERP). If MRP II is adopted, there is a 73.4% chance that ERP is also adopted. This means that firms are focussing of the software aspect to ensure they can have a complete view of their firm in one software. Although ERP is not only specific to manufacturing, companies that are in the manufacturing industry will probably have an MRP II that is integrated with their ERP system or that is stand-alone. The other top bundles all contain both of the technologies discussed previously, which means that resource planning technologies are important for firms. However, ERP is adopted a lot more than MRP II due to the fact that it works with many types of industries as opposed to MRP II that is very specific to manufacturing. For instance, an engineering service firm in the construction industry uses a CAD software to design their electrical conduits in a building, but will not need to adopt an MRP II as they are not the ones doing the construction.

Table 6.16: Design and Information Control top 15 association rules sorted by support

	LHS		RHS	Support	Confidence	Lift	Count
S1	{MRPII}	=>	{ERP}	0.154	0.734	1.710	586
S2	{ERP, WCP}	=>	{EDI}	0.119	0.713	1.350	455
S3	{EDI, MRPII}	=>	{ERP}	0.099	0.749	1.743	378
S4	{CAX, MRPII}	=>	{ERP}	0.095	0.766	1.785	361
S5	{VM}	=>	{CAX}	0.091	0.884	1.793	349
S6	{EDI, SI}	=>	{ERP}	0.083	0.703	1.637	315
S7	{CIM, EDI}	=>	{CAX}	0.082	0.705	1.431	313
S8	{WCP, WSN}	=>	{EDI}	0.080	0.718	1.359	306
S9	{EDI, WSN}	=>	{WCP}	0.080	0.730	2.030	306
S10	{CAX, SI}	=>	{ERP}	0.076	0.729	1.698	291
S11	{ERP, WSN}	=>	{EDI}	0.075	0.732	1.386	287
S12	{CIM, ERP}	=>	{CAX}	0.075	0.720	1.460	285
S13	{ERP, WSN}	=>	{WCP}	0.074	0.722	2.007	283
S14	{SI, WCP}	=>	{EDI}	0.073	0.736	1.393	279
S15	{SI, WCP}	=>	{ERP}	0.072	0.726	1.690	275

The last part of the analysis explored the mapping of the 57 rules that corresponded to the minimum thresholds of support and confidence. The network in Figure 6.13 illustrates the global view of how DIC technologies are connected. Despite seeing that VM was included in rules with a high confidence, it is only visible three times on the graph (e.g. rules R5, R41, R44). These previous rules were not the most popular ones, and this can be explained by the fact that firms prefer using CAX technologies in general. It is worth mentioning that UAS did not figure in any of the rules in the graph, which can be explained by a few possible causes. First, this technology was by far the least adopted amongst all. It could be due to the fact that drones were not as popular back when the survey was made around 2014. Moreover, it might have been only adopted by early adopters and the support of bundles containing this technology could have been even lower than the threshold of 0.05. As previously mentioned, EDI was at the centre of the network with many rules around it. The same can be said for WCP that provides a way for machines to transmit data. Although more specific to manufacturing, it still has a high adoption rate and is comprised in many rules. The importance of ICT in the exchange of data, voice and image has been emphasized in the literature (Bardhan, Krishnan, & Lin, 2007; Bouwman, Van Den Hooff, Van De Wijngaert, & Van Dijk, 2005; Johannessen, 1994; Sproull, Kiesler, & Kiesler, 1991).

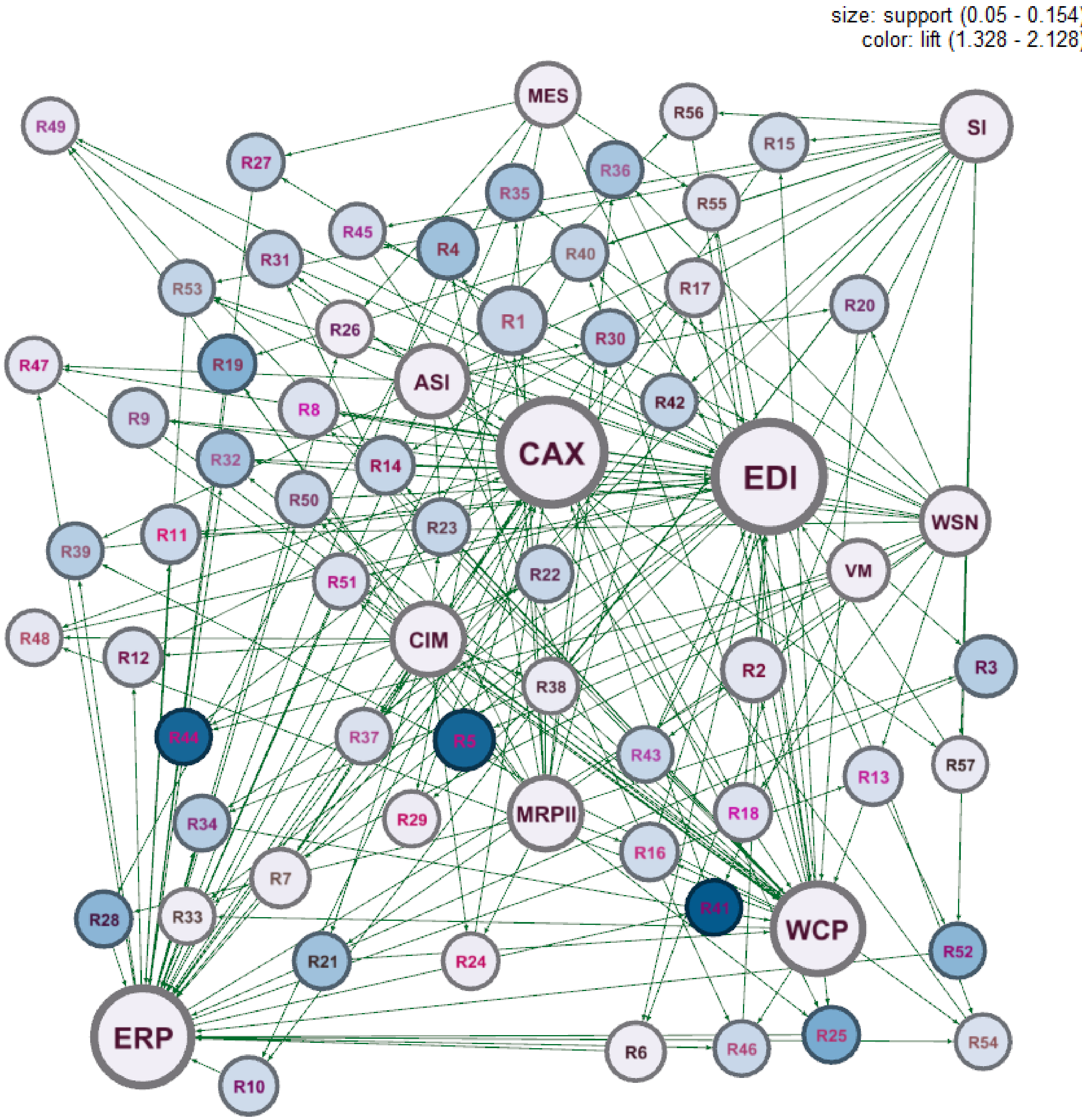

Figure 6.13: Design and Information Control association rules network

Table 6.17: Design and Information Control association rules with a confidence of 1

ID	LHS		RHS	Support	Confidence	Lift	Count
1	{ASI, MRPII, VM, WSN}	=>	{CIM}	0.012	1.000	4.850	44
2	{MES, MRPII, SI, VM, WSN}	=>	{CIM}	0.012	1.000	4.850	45
3	{ERP, MES, MRPII, VM, WSN}	=>	{CIM}	0.012	1.000	4.850	45
4	{ERP, MES, MRPII, SI, VM, WSN}	=>	{CIM}	0.011	1.000	4.850	41
5	{SI, UAS}	=>	{EDI}	0.010	1.000	1.892	40
6	{ASI, ERP, MRPII, VM, WSN}	=>	{CIM}	0.010	1.000	4.850	40
7	{CAX, MES, MRPII, SI, VM, WSN}	=>	{CIM}	0.010	1.000	4.850	40
8	{EDI, MES, MRPII, SI, VM, WSN}	=>	{CIM}	0.010	1.000	4.850	39
9	{CAX, ERP, MES, MRPII, VM, WSN}	=>	{CIM}	0.010	1.000	4.850	40

In order to understand the least adopted technologies, the algorithm can be configured to find rules that have a confidence of 1. A confidence of 1 means that if the technologies in the antecedent portion of the rules are adopted, there is a 100% chance that the consequent technology will be adopted too. The minimum support threshold was set to 0.01, which generated 9 rules (see Table 6.17). The most striking finding is that these rules are comprised of more technologies than with previous thresholds. With the exception of rules 1 and 5, all rules include six or seven technologies. This can indicate larger firms or very specialized ones that can afford having all these technologies. Second, UAS is present for the first time (e.g. rule 5) and alongside SI and EDI, has only been adopted by 40 firms. SI is the integration of tools for quality tests while UAS can be very useful technology to verify to quality of a product during and after manufacturing. These 40 firms could be early adopters of these technologies. For the other eight rules, CIM is always a consequent, with a confidence of 1. In other words, when firms have adopted these different combinations, there is a 100% chance that CIM is also adopted. Being a tool that integrates the manufacturing process with a computer, it makes sense from a practical standpoint that when a firm has all the different pieces together, they would also have the tool that can do the integration. In all cases, the lift is higher than 1 and apart from rule 5, these rules have a lift value of 4.85. This points towards a strong dependency between the consequents and antecedents.

6.4 Processing and Fabrication technologies

Similar to DIC, Process and Fabrication technologies (PF) technologies comprise 12 different technologies. Due to their very advanced nature and broad usage, there is an expectation to find many different bundles including 3D printing and other advanced manufacturing techniques. Figure 6.14 shows the adoption rate of each technology. In general, PF technologies have been the least adopted category by firms. Most technologies have been adopted by very few companies. Apart from CNC that has been adopted by almost 50% of firms, all other technologies are around 25% adoption rate and even lower. Some technologies even have an adoption rate as low as 5%, such as MM, 3DO and MEMS. These are highly specialized manufacturing techniques that require specific core activities in highly advanced industries such as the pharmaceutical and the semiconductor sectors.

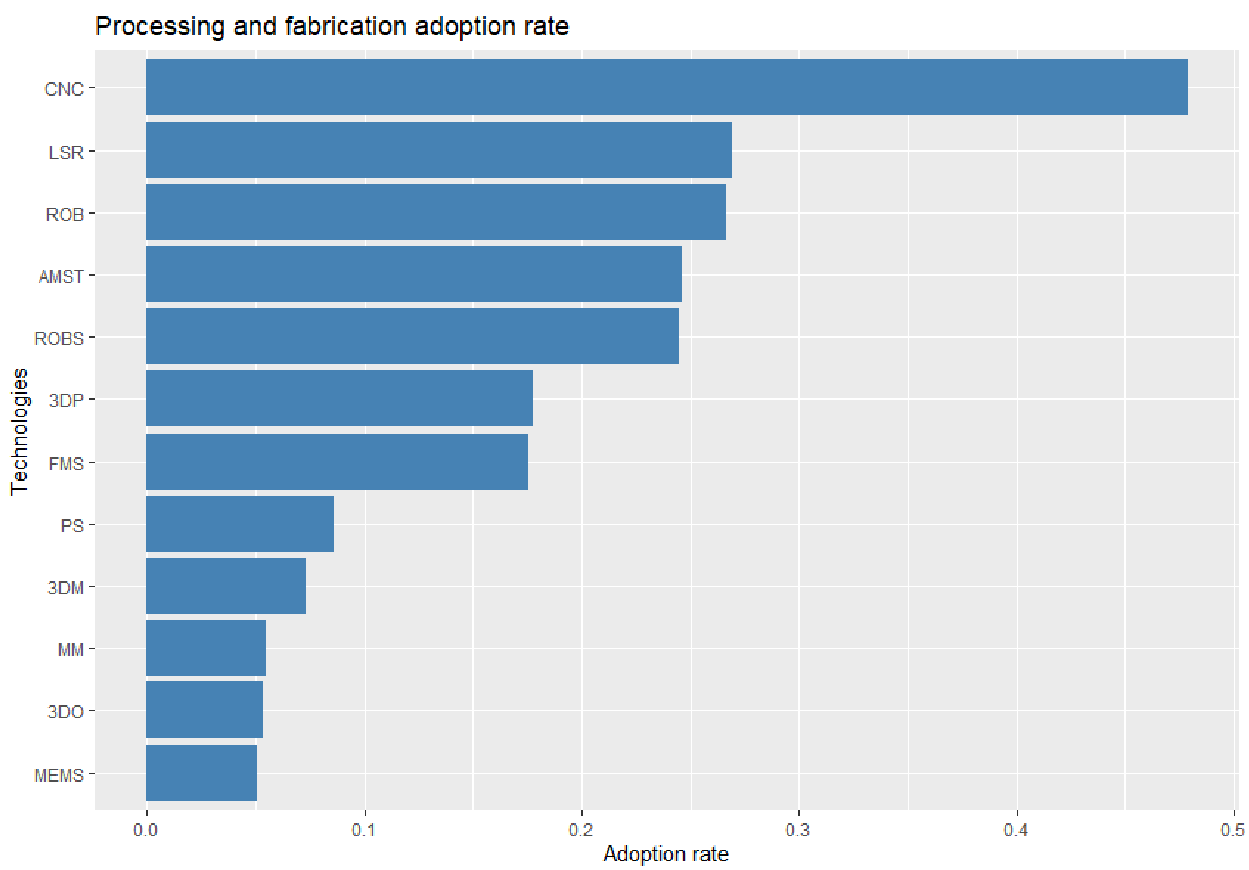

Figure 6.14: Frequency plot of Process and Fabrication technologies

From the 1520 firms that adopted PF technologies, more than 80% adopted three or fewer technologies while less than 6% adopted six or more technologies (see Table 6.18). These technologies can be expensive and at the time of the survey, advanced manufacturing was just starting as the trend was shifting towards Industry 4.0. Because of that, expected rules generated should not contain more than three or four technologies foremost. One of the reasons why the adoption rates of PF technologies are low can be because of their price tag. They often require complex machinery that needs to be integrated with a software. Another reason can be that these technologies are very specialized to specific industries, namely the ones that require advanced and micro-manufacturing. Therefore, if a firm’s core business activities do not fall into Industry 4.0, it can explain the low adoption rates. To study this pattern, the different bundles of adopted technologies need to be explored by computing the association rules *apriori* algorithm.

Table 6.18: Design and Information Control technologies - Item sets length distribution

Length	Frequency	Percentage
1	780	51.32%
2	295	19.41%
3	178	11.71%
4	107	7.04%
5	75	4.93%
6	41	2.70%
7	24	1.58%
8	9	0.59%
9	1	0.07%
10	7	0.46%
12	3	0.20%
Total	1520	100%

In total, there are 24432 possible rules that were generated using a support and confidence thresholds of 0 (see Figure 6.15) in which there are a few rules with a confidence of 1. However, their support seems to be very low. Rules with a confidence of 1 can include technologies adopted by highly specialized firms. There are few rules with a support higher than 0.3 and only one rule with a support higher than 0.4. Furthermore, most of the rules with a high confidence (higher than 0.8) have a support lower than 0.1. From Figure 6.15, it seems that low support rules need to be explored in order to get a high confidence. To decide on the thresholds that will be used, the distribution of rules needs to be examined by varying support and confidence thresholds.

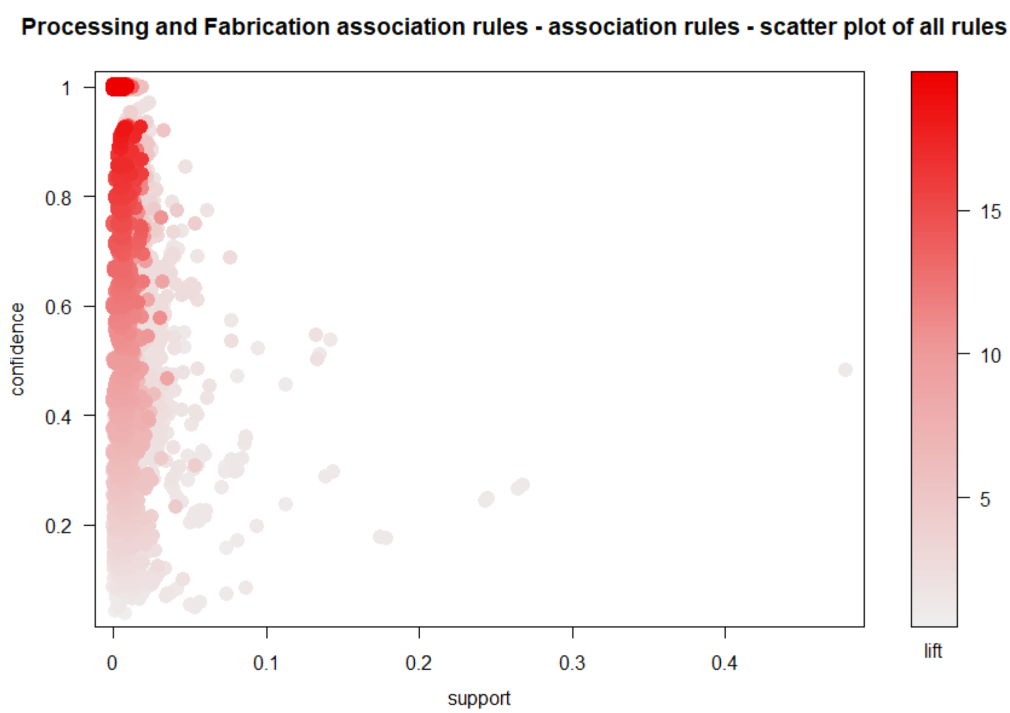

Figure 6.15: Processing and Fabrication association rules – scatter plot of all rules

Table 6.19 shows the distribution of rules by changing the support and the confidence. There are a very few rules generated using a confidence of 0.6 and a support of 0.05. To obtain more rules a support of 0.025 and a confidence of 0.6 can be used. However, these thresholds will not include the rules that had a confidence of 1, which means the algorithm will need to be run a second time with no minimum support threshold and a confidence of 1. To stay consistent with the other technologies, a support of 0.025 and a confidence of 0.6 were used. This generates a total of 59 rules that can be analyzed.

Table 6.19: Distribution of Design and Information Control association rules by confidence and support

	Confidence		
Support	**0.4**	**0.6**	**0.8**
0.025	136	59	6
0.05	22	8	0
0.1	6	0	0

The 59 rules that were generated are sorted by confidence (see Table 6.20) and by support (see Table 6.21). As with other categories of technologies, only the top 15 rules are shown in the tables. Analyzing the rules sorted by confidence in Table 6.20, the first rule (C1) is definitely the most interesting one in the context of industry 4.0. In fact, technologies 3DM, 3DP and 3DO represent the different types of 3D printing, whether it's applied to plastics, metals or other materials. Adopting 3DM and 3DO gives a 92.3% chance that 3DP will be adopted as well. The firms adopting this bundle are expected to be in highly specialized firms that sell a 3D printing service or that use it themselves to manufacture products that are made of different material types. It is worth mentioning that 3D printing adds flexibility to the manufacturing process, which is not only achieved by the speed of manufacturing but also by the different materials that can be used. The rules containing 3D printing technologies allow to differentiate between the two purposes that were previously mentioned, namely rapid prototyping (RP) and rapid manufacturing (RM). The literature distinguishes both techniques due to the fact that RM accelerates the manufacturing of products with long-term consistency (Levy et al., 2003). It is only logical for a firm adopting type of 3D printing to also adopt the others if they want to have maximum flexibility in terms of materials being used. Rules that include 3D printing without CNC could be companies that aim to be more disruptive by using AM to create fully customized products. For instance, not only has rule C1 high confidence but a high lift as well, suggesting a strong complementarity between these

3D printing technologies. There are only 48 firms that have adopted this bundle, which represents only 3.2% of the total number of firms who adopted PF technologies. Considering Industry 4.0 might have started to get more popularity in 2014, it can be said that these 48 firms are early adopters of 3D printing and are potentially using it as a disrupting technology to rapidly manufacturing parts for their final products. For instance, C1 is a rule that doesn't include CNC, which suggests that 3D printing is used as RM tool by these companies. Moreover, Hopkinson and Dicknes (2003) found that in some cases, it is more economical to use RM methods instead of traditional approaches, suggesting that AM seems appropriate for low-volume production because the cost of production is considered constant, whereas the cost of using CNC machinery is amortized across a large production volume. This can further explain why some companies adopt 3D printing technologies without having a CNC because they produce smaller volumes. These firms are expected to be smaller firms with more disrupting products.

There are other bundles in Table 6.20 that contain a 3D printing technology, one of them being C14. Because it is exactly the same bundle as rule C1, the support remains the same at 3.2%. However, the confidence is slightly lower whereas the lift is much higher. If a firm adopted 3DP and 3DO, they have 76.2% chance of adopting 3DM technology. The first interpretation from rules C1 and C14 is that firms who have adopted 3D printing for metals have a higher chance to have also adopted 3D printing for plastics (confidence = 92.3%) than the other way around (confidence = 76.2%). It appears that firms adopting 3DM often requires the flexibility to also adopt 3DP, while 3DP might be enough in more cases on its own. Another interesting fact is that CNC technology is almost always a consequent in the top 15 rules displayed. From a practical standpoint, it makes sense because CNC widely used in traditional supply chains. As was previously mentioned, CNC is seen as a traditional supply chain technology that relies on a subtractive process (Reeves, 2009) as opposed to the additive and more advanced process of 3D printers. Rules that combined CNC and 3D printing technologies are expected to be firms that use additive manufacturing (AM) for RP purposes as stated above. Rapid prototyping makes it possible to test products in their development phase but are not meant to be incorporated in the end products. For example, rule C2 shows that the use of LSR (Lasers) and ROB (robots without sensing or vision systems) and 3DP can be present in complementarity with a CNC for quality checks. This can be an example of a firm that is using 3DP as an RP tool to help with the product development phase tool and then combining with traditional machinery, such as CNC.

Furthermore, FMS (e.g. C5, C10) represents a manufacturing process that is flexible. These systems or cells are comprised of multiple CNC that allow firms to customize their products according to their customer's needs. In rule C5, the fact that FMS, LSR and ROBS are adopted means that there is an 83% chance that CNC is also adapted. Although it's not a certainty, it still shows a lot of complementarity between these technologies. Finally, it is worth noting that this combination is one of the least adopted technologies, which further points to early adopters of Industry 4.0 at the time of the survey. Moreover, only 7.04% of firms adopted four technologies, which can also highlight the high investment required to adopt many AMTs.

Table 6.20: Processing and Fabrication top 15 association rules sorted by confidence

ID	LHS		RHS	Support	Confidence	Lift	Count
C1	{3DM,3DO}	=>	{3DP}	0.032	0.923	5.197	48
C2	{3DP, LSR, ROB}	=>	{CNC}	0.027	0.891	1.861	41
C3	{3DO, ROB}	=>	{CNC}	0.026	0.886	1.851	39
C4	{MM}	=>	{CNC}	0.047	0.855	1.786	71
C5	{FMS, LSR, ROBS}	=>	{CNC}	0.026	0.830	1.733	39
C6	{CNC, FMS, ROBS}	=>	{ROB}	0.028	0.811	3.045	43
C7	{LSR, ROB, ROBS}	=>	{CNC}	0.040	0.792	1.654	61
C8	{AMST, LSR, ROB}	=>	{CNC}	0.027	0.788	1.646	41
C9	{3DM, LSR}	=>	{3DP}	0.026	0.780	4.391	39
C10	{FMS, LSR, ROB}	=>	{CNC}	0.026	0.780	1.629	39
C11	{3DO}	=>	{3DP}	0.041	0.778	4.379	63
C12	{LSR, ROB}	=>	{CNC}	0.062	0.772	1.613	95
C13	{3DP, ROB, ROBS}	=>	{CNC}	0.028	0.768	1.603	43
C14	{3DO, 3DP}	=>	{3DM}	0.032	0.762	10.433	48
C15	{FMS, ROB, ROBS}	=>	{CNC}	0.028	0.754	1.575	43

As seen with other technologies, shifting the analysis to the most frequently adopted bundles, the confidence decreases by a good margin for most rules. There is a rule with a slightly higher support (e.g. S1 with a support of 0.07 in Table 6.21) compared to the rest of the rules. However, it still represents a very small portion of firms that adopted PF technologies. In fact, the most popular rule is comprised of ROBS and CNC with ROB as a consequent technology. As was mentioned previously, robots can have multiple functions in advanced manufacturing, some of them requiring sensing systems while others don’t. When robots with sensing are adopted, there is a good chance that robots without sensing are adopted as well. Furthermore, there are a lot of robots being adopted as consequent. Robots without sensing can do tasks such as wielding or arcing by manipulating objects and materials, in which case sensing is not always required. It is easier to access for firms because it is less expensive than sensing systems. Finally, the most important aspect in the rules sorted by support is there are fewer rules containing 3D printing technologies. While 3D printing technologies seemed to be highly complementary, there are very few firms adopted these in general and there are even less present in bundles. It can be argued that this type of technology was only used by early adopters that found a certain niche for their specific industries. Clearly, adopting more than one 3D printing technology (e.g. 3DM, 3DP, 3DO) is a popular choice, this family of technologies did not have the highest adoption rate within the PF category.

Table 6.21: Processing and Fabrication top 15 association rules sorted by support

ID	LHS		RHS	Support	Confidence	Lift	Count
S1	{CNC, ROBS}	=>	{ROB}	0.077	0.688	2.583	117
S2	{LSR, ROB}	=>	{CNC}	0.062	0.772	1.613	95
S3	{3DM}	=>	{3DP}	0.055	0.748	4.210	83
S4	{LSR, ROBS}	=>	{CNC}	0.055	0.692	1.444	83
S5	{AMST, ROBS}	=>	{ROB}	0.054	0.612	2.297	82
S6	{AMST, ROB}	=>	{ROBS}	0.054	0.631	2.577	82
S7	{LSR, ROBS}	=>	{ROB}	0.051	0.642	2.408	77
S8	{LSR, ROB}	=>	{ROBS}	0.051	0.626	2.558	77
S9	{MM}	=>	{CNC}	0.047	0.855	1.786	71
S10	{AMST, CNC}	=>	{ROB}	0.047	0.637	2.391	72
S11	{AMST, CNC}	=>	{ROBS}	0.046	0.619	2.531	70
S12	{3DP, ROB}	=>	{CNC}	0.044	0.736	1.537	67
S13	{3DO}	=>	{3DP}	0.041	0.778	4.379	63
S14	{3DP, LSR}	=>	{CNC}	0.041	0.708	1.478	63
S15	{LSR, ROB, ROBS}	=>	{CNC}	0.040	0.792	1.654	61

The last part of the analysis focusses at the graph displaying the 59 rules that correspond to the minimum thresholds of support of confidence. The network in Figure 6.16 shows a global view of how PF technologies are connected. There are many different technologies such as CNC, LSR and ROB/ROBS that are the centre of the network because they have connections with many rules. However, there are clearly two technologies, MEMS and MM, that are isolated from the network. These technologies are amongst the least adopted within PF category. Furthermore, they only link to one rule each. This can indicate their level of complexity, suggesting firms do not have the right resources to adopt them. It can also mean that there is a cost issue although other technologies in the PF category require a lot of investment also. Despite a relatively low adoption rate, 3D printing technologies are present in many rules as well, which indicates that they have complementarities with the rest of the advanced manufacturing technologies. In fact, 3D printing is often used to do rapid-prototyping and it can be used in combination with FMS for example to produce products at a larger scale. Furthermore, 3D printing technologies use lasers to modify and alter the properties of the materials used to produce a prototype so it would only make sense to be used in combination with LSR technology. Other technologies that are complementary with 3D printing include, ROB and CNC. When a bundle includes ROB, CNC and 3DP, it means that this firm has a developed and automated manufacturing process that included rapid-prototyping and software integration. This not only adds quality but also flexibility to a product and allows for a quick customization and adaptation to customers' demands.

Table 6.22 displays the most popular rules with a confidence of 1. Because the confidence level has been increased, these rules represent a high complementarity between the technologies adopted despite having a very low support. These rules should be taken with a grain of salt because they only represent between 20 and 29 firms that have adopted these specific bundles.

Table 6.22: Processing and fabrication association rules with a confidence of 1

ID	LHS		RHS	Support	Confidence	Lift	Count
1	{3DM, 3DO, LSR}	=>	{3DP}	0.019	1.000	5.630	29
2	{MM, ROB, ROBS}	=>	{CNC}	0.017	1.000	2.088	26
3	{3DM, 3DO, AMST}	=>	{3DP}	0.016	1.000	5.630	25
4	{LSR, MM, ROBS}	=>	{CNC}	0.014	1.000	2.088	22
5	{FMS, MM}	=>	{CNC}	0.013	1.000	2.088	20
6	{LSR, MM, ROB}	=>	{ROBS}	0.013	1.000	4.086	20
7	{LSR, MM, ROB}	=>	{CNC}	0.013	1.000	2.088	20
8	{LSR, MM, ROB, ROBS}	=>	{CNC}	0.013	1.000	2.088	20
9	{CNC, LSR, MM, ROB}	=>	{ROBS}	0.013	1.000	4.086	20

For instance, rule 1 shows that if 3DM, 3DO and LSR are adopted, there is a 100% chance that 3DP is also adopted as well. It combines the three types of 3D printing together with lasers which could be explained by a niche industry. As previously mentioned, LSR are an important part of 3D printers in general. There are also more rules that include MM, one of the least adopted technologies in the PF category. Seven out of nine rules comprise MM with other technologies such as LSR, ROB(s), FMS and CNC. Most of the time, CNC is a consequent to these rules suggesting the integration of many different technologies included in the manufacturing process. For instance, LSR are used to change a material's properties while ROB(s) are robots that can perform tasks such as yielding or arcing. Finally, a CNC can be an individual machine or integrated as part of an FMS to add more flexibility. In either way, these technologies require integration through a CNC and this is why it makes sense to find these with a very high confidence. It can be said that the core technologies of advanced manufacturing comprise ROB(s), LSR, CNC, while MM, 3D printers and others are specific to a case-by-case manufacturing capabilities of the firm in question.

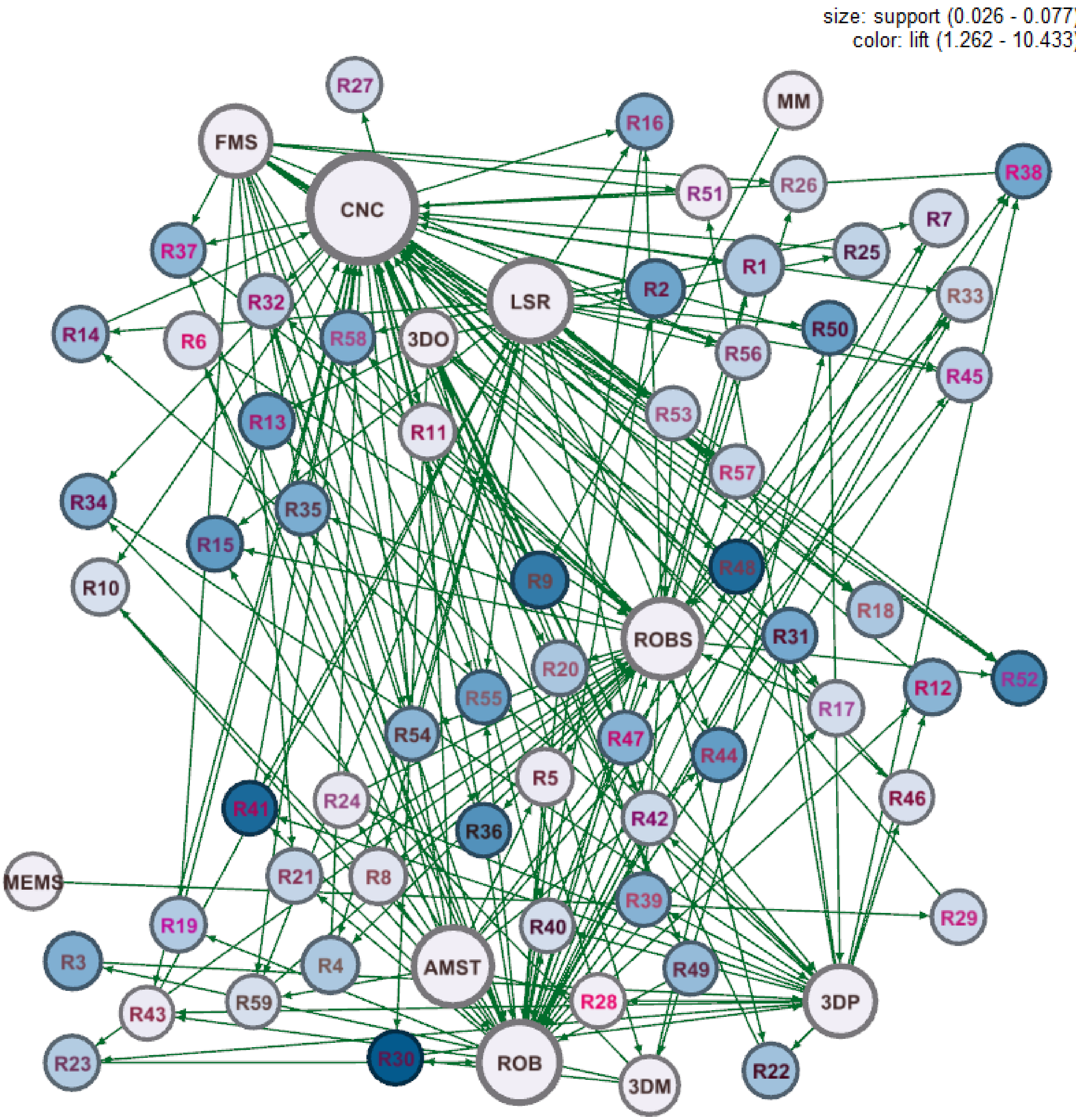

Figure 6.16: Processing and Fabrication association rules network

6.4.1 Descriptive statistics of PF technologies

Figure 6.17 shows the most frequent PF technologies bundles and their adoption rate. The bundles and technologies are exclusive meaning that only the technologies displayed were adopted. As we previously mentioned, more than 52% of firms have only adopted a single technology (see Table 6.18), which is confirmed in this figure because there are five single technologies that have a combined adoption rate of 35%.

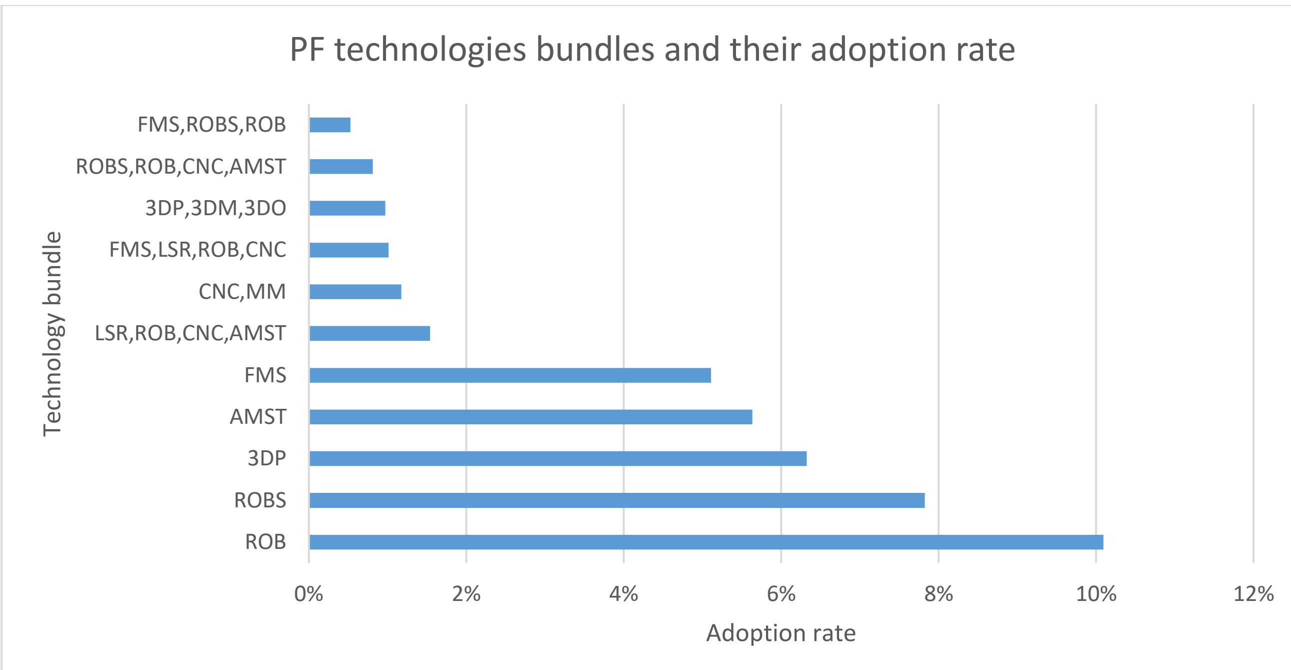

Figure 6.17: Most frequently adopted PF technologies bundles (exclusive technologies)

Table 6.23 shows what characterizes firms that have decided to adopt some specific bundles of technologies. For example, it can be noted that firms who have adopted FMS, independently from other technologies, seem to be older with an average age of 20.75. However, once other technologies are added, the age changes. In fact, adding ROBS and ROB decreases the average age to 18.10, although it is only 13 firms in that situation. Other bundles that have similar technologies such as in bundles 2,3,5,6 have different age average, which means that firms are in general adopting “à la carte” technologies.

In terms of revenue, firms having adopted bundle 5 seems to have the biggest average revenue in general. In terms of size, firms having adopted the bundles displayed in Table 6.23 have more employees than other firms in general. In fact, firms that adopted LSR, ROB, CNC and AMST (i.e. B5) have on average a total of 733 employees, which could indicate that the number of PF technologies adopted might be positively correlated to the size of the firm. However, this is not something that can be concluded from the current analysis. The results also showed that 3D printing is accessible, because even firms with a lower revenue have adopted these technologies (e.g. B8, B10). For instance, B10 contained two types of 3D printers and has been adopted by firms with an average revenue of 7M. The results need to be interpreted with caution, however, as only 10 firms have adopted these two technologies together.

Table 6.23: Adopted PF bundles according to age, revenue and size

ID	Bundles	age	revenue	size	N
B1	FMS	20.75	21M	58.83	124.00
B2	FMS, LSR, ROB, CNC	11.15	87M	131.14	25.00
B3	FMS, ROBS, ROB	18.10	261M	448.13	13.00
B4	ROBS	19.57	46M	109.13	192.00
B5	LSR, ROB, CNC, AMST	16.11	1250M	733.35	36.00
B6	ROBS, ROB, CNC, AMST	22.08	94M	129.68	20.00
B7	ROB	17.94	67M	123.61	244.00
B8	3DP	14.39	35M	104.18	154.00
B9	3DP, 3DM, 3DO	16.62	283M	110.51	24.00
B10	3DP, 3DO	15.85	7M	40.49	10.00
B11	AMST	16.73	31M	93.12	139.00
B12	CNC, MM	14.32	18M	59.43	29.00

Figure 6.18 shows the innovation type based on the bundles adopted. Firms who have adopted PF technologies in general seemed to have a better propensity to innovate. Comparing these bundles to all other firms including those who adopted or not PF technologies, it should be noted that their innovation propensity is higher on average. In the case of the first two bundles, there are respectively 100% and 99% of firms that have introduced any type of innovation. The reader should recall that these bundles have only been adopted by a select few companies, which needs to be

taken into consideration before arriving at the conclusion that firms adopting these specific bundles of PF technologies have a high propensity to innovate.

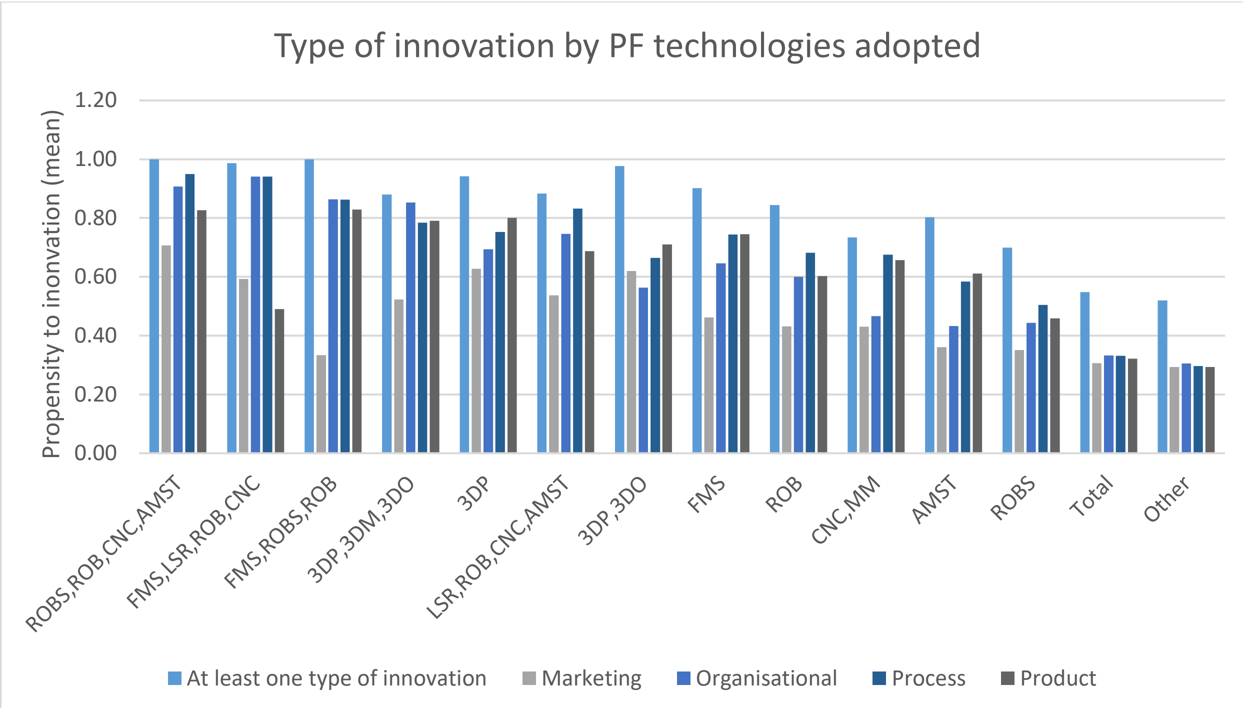

Figure 6.18: Type of innovation by PF technologies adopted

6.5 Comparing planning to adopt vs. adopt only

The data set used allows to add the concept of temporality. In other words, the survey provides information on whether a firm is already using a technology or if it plans to adopt it in the future. The results presented up to now considered that a firm adopted a technology if it was in use for more than three years and for less than three years. In this section, the same steps with the *apriori* algorithm will be repeated, but by considering the technologies that firms are planning to adopt and comparing them to the initial results found. The goal is to analyze which technologies are firms adopting and when they are doing it. For instance, some BI and PF technologies did not have a high adoption rate in 2014 could show up more often in bundles when analyzing what firms were planning to adopt to 2016. In the case of PF technologies especially, it should be noted that some differences may arise because Industry 4.0 was just starting in 2014. In other words, firms may not have adopted more advanced manufacturing technologies but planned to do so in the future. This type of analysis only focusses on two categories of technologies, namely BI and PF because they both have technologies that had a low adoption rate (e.g. BDS for the BI technologies; MM, 3D, PS for PF technologies).

Business Intelligence

Figure 6.19 illustrates what firms were using at the time of the survey compared to the bundles they planned on using in the future. No additional firms planned on adopting the bundle SaaS and IaaS, which means that it was already popular at the time. However, most of the firms were planning to adopt bundles of more than two technologies amongst which SaaS and IaaS are included in every bundle. SaaS and IaaS being very popular and also very accessible, firms planned on adopting them in the future but in combination with other important technologies such as ED and RTM. Despite the importance of BDS for implementing AI in the future, the most frequently planned bundles do not include this technology. However, there are three bundles of four or five technologies that include BDS, suggesting that firms planning on adopting all these BI tools may be looking to implement AI in the future.

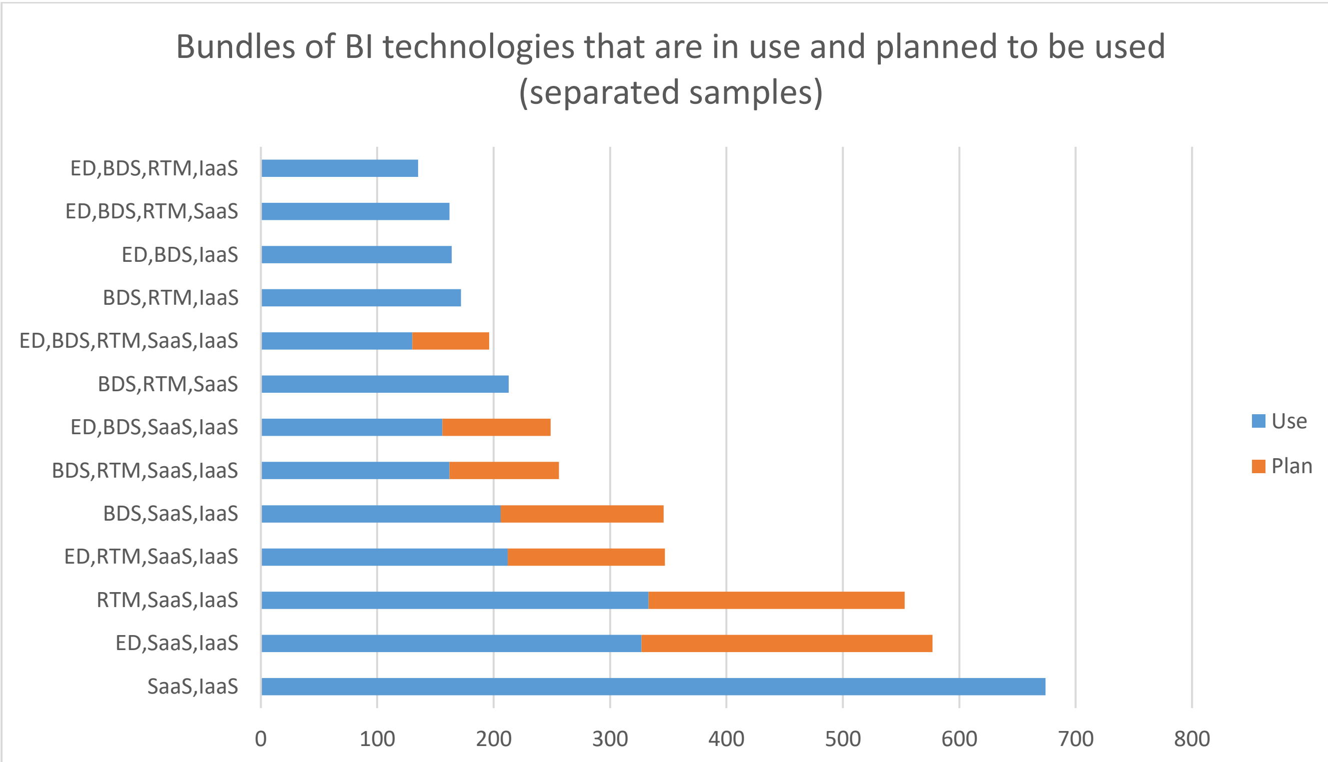

Figure 6.19: Bundles of BI technologies in use and planned to be used (separate samples)

To get a more accurate view, Figure 6.20 shows the association rules considering that firms that adopted or planned to adopt are users of the technology. This gives an idea of the picture of adopted technologies in 2016, assuming that firms that were planning to adopt them did use them. Unsurprisingly, the most frequently adopted bundle remains SaaS and IaaS. This can be due to the many software available that offers a version in the cloud. SaaS continued to grow over the years and many software companies have made a cloud version of their flagship software. In other words, this weakens the relevance of having SaaS or IaaS as a part of single technology. Most of the software applications available on the market are mainly, if not uniquely, offered as a cloud service. Another very popular bundle, which can be seen from what firms planned to adopt in Figure 6.19, is RTM and ED technologies. These two technologies are very important to collect, view and analyze data. Firms also choose to combine RTM and ED with SaaS and IaaS, which is expected as these tools can also be offered in the cloud. The last technology that seems to be getting more popular is BDS. As was previously mentioned, BDS is an essential tool for the adoption of artificial intelligence when a large volume of data is involved. Even though it started to be seen more widely adopted in bundles, it was probably still in its early stages at the time of the survey. This could result into lower adoption rate of artificial intelligence in Canada even today in 2020, because BDS can take a lot of time to implement. It should be noted that the adoption of RTM can also be viewed as an essential aspect to AI. Because RTM collects data in real-time, it is expected that companies will implement strategies to quickly analyze this data and guide them through their decision-making process. There are 8 bundles out of the top 15 rules (see Figure 6.20) that include BDS, while there were only 4 rules including BDS when compared to association rules that were generated for technologies in use only. This suggests an important increase in BDS adoption, not only individually but as part of larger BI bundles that are necessary for AI adoption. These results highlight the importance this technology in the future because of how many firms were planning to adopt it at the time of the survey. It also points towards its complexity or the lack of trained workforce to implement such a tool in the year 2014. Finally, it should be noted that there were no new frequently adopted bundles of technologies that were planned to be adopted when analyzing Figure 6.19, suggesting that BI technologies were mostly mature enough amongst firms at the time of the survey. Despite the low adoption of BDS, firms knew that it was an important technology and were planning to adopt it. This is to be interpreted with caution because there are only five BI technologies, which makes it easier for most combinations to be already adopted.

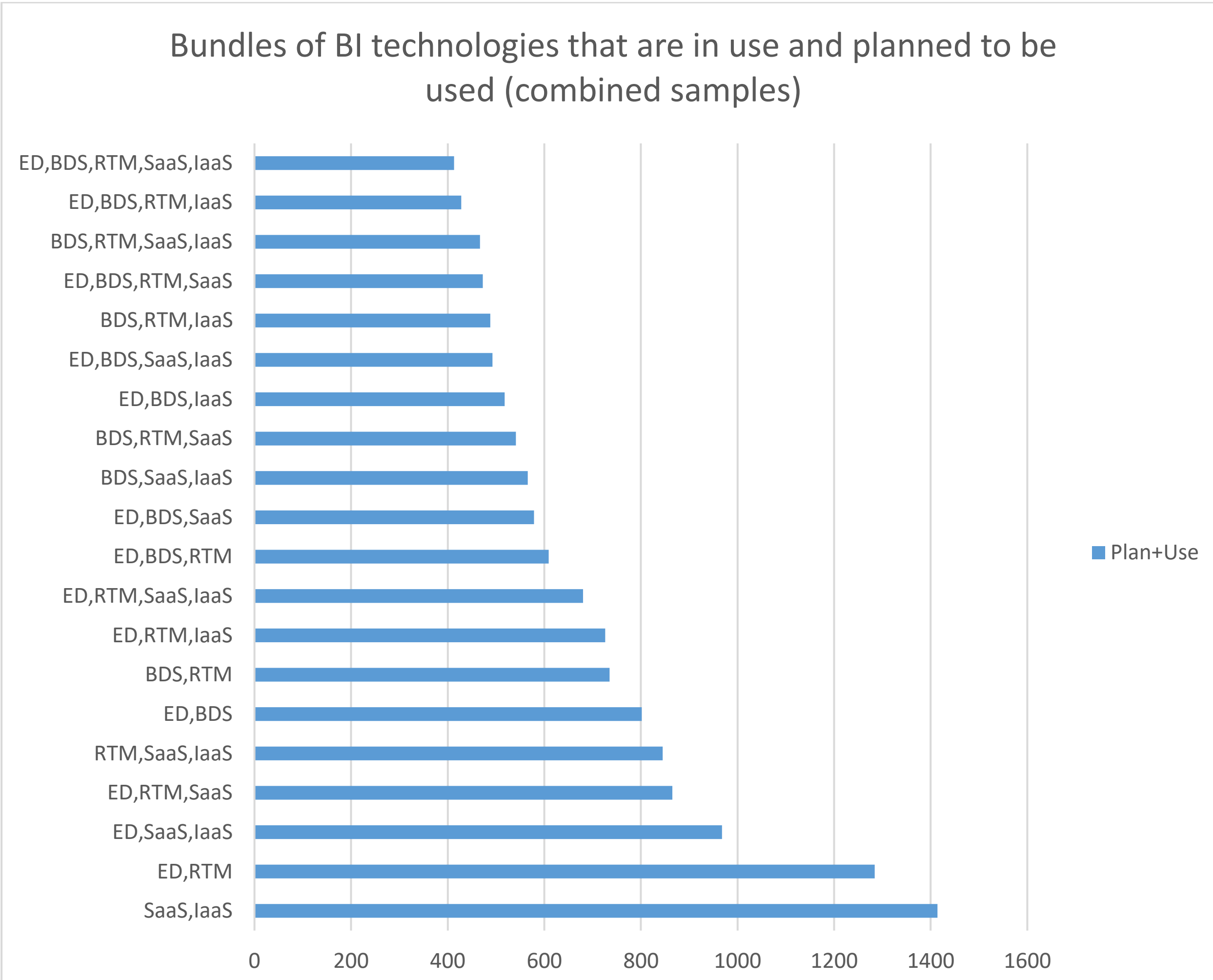

Figure 6.20: Bundles of BI technologies that are in use and planned to be used (combined samples)

Processing and Fabrication

Figure 6.21 shows what firms were using at the time of the survey compared to the bundles they plan on using. At the time of the survey, firms were already using 3D printing technologies such as the bundle 3DP, 3DO. There was another bundle containing all three forms of 3D printing that was more frequently adopted as well. However, analyzing what firms were planning to use, it should be noted that a lot more bundles included 3D printing technologies. For instance, there are eight new rules (in orange) that are all comprised of at least one type of 3D printing. Furthermore, the most popular 3D printing bundle adopted is by far the most popular bundle planned to be adopted. This suggests the importance 3D printing is taking into a firm's future adoption strategy. However, it should be noted that it does not mean that it will be the most frequently adopted group of technologies. To confirm what is being highlighted, the *apriori* algorithm needs to be run another time considering a combined sample of firms that adopted and those that plan to adopt. Computing association rules with a combined sample contributes to increasing the sample size because firms planning to adopt two years in advance are considered. This is especially important because the adoption rate of PF technologies is low and increasing the sample increases the adoption rate consequently.

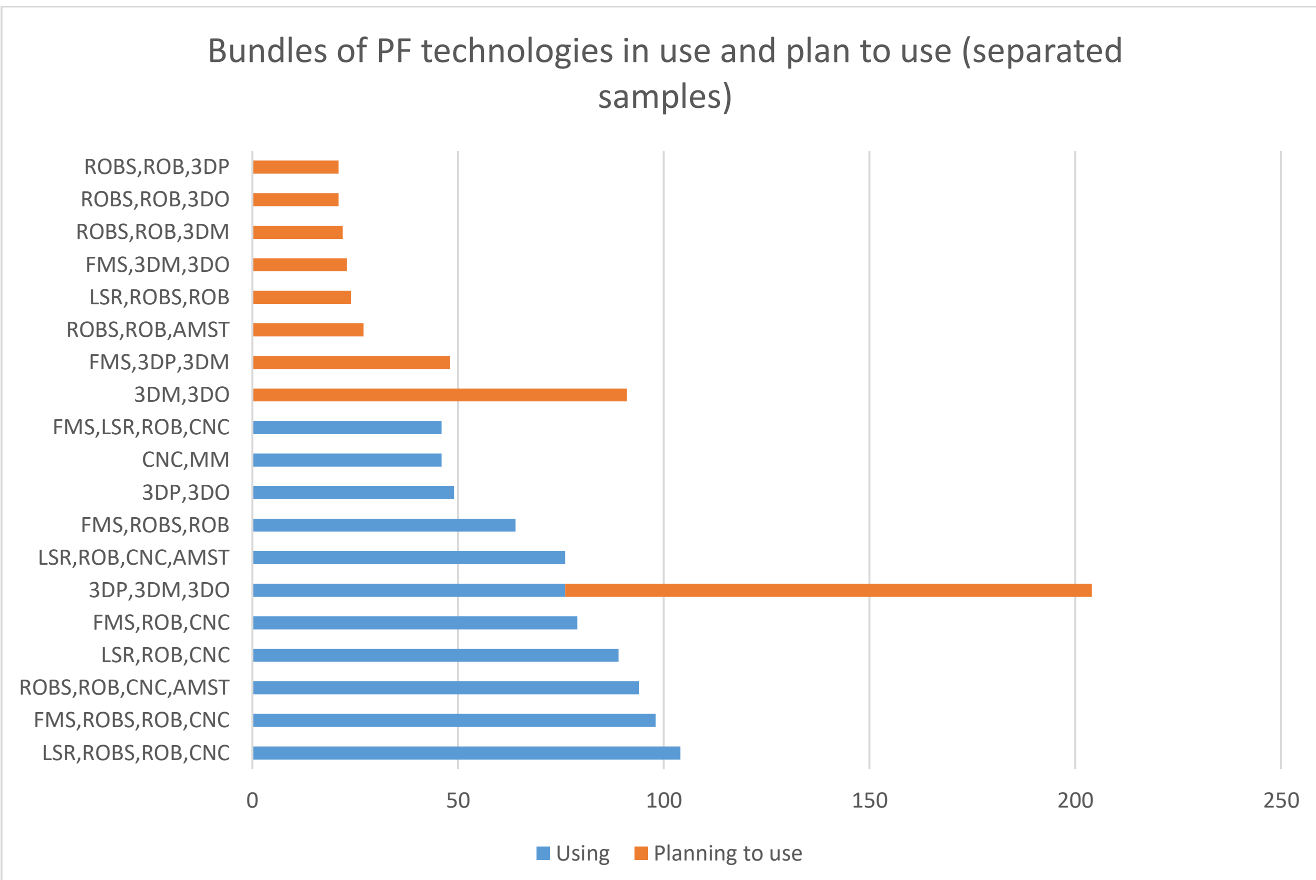

Figure 6.21: Bundles of PF technologies in use and planned to be used (separated samples)

The results display the number of firms that have adopted (or planned to adopt) each bundle because as the sample size by including firms that plan to adopt increases, the total number of firms that have adopted PF technologies increases. It should be noted that the most popular bundles are still similar to what was previously found. However, the most frequent bundle now contains 3D printing technologies for metals and plastics (3DP, 3PM) combined with robots with and without sensing (ROBS, ROB). Analyzing the top 10 bundles, six of them comprise 3D printing technologies. In the previous graph (see Figure 6.21), only 2 out of the top 10 bundles had these technologies. The strong motivation for firms to adopt 3D printing can be argued because the most popular bundle planning to be adopted had the three types. However, analyzing what companies had already adopted and what they plan to adopt as a whole, it can be observed that many core technologies such as ROB(S), LSR, FMS and CNC remain the same but with 3D printing added into the mix. This gives an insight into the beginning of industry 4.0. As was previously mentioned, only early adopters had 3D printing technologies while two years after the survey was done, many firms were planning to adopt it.

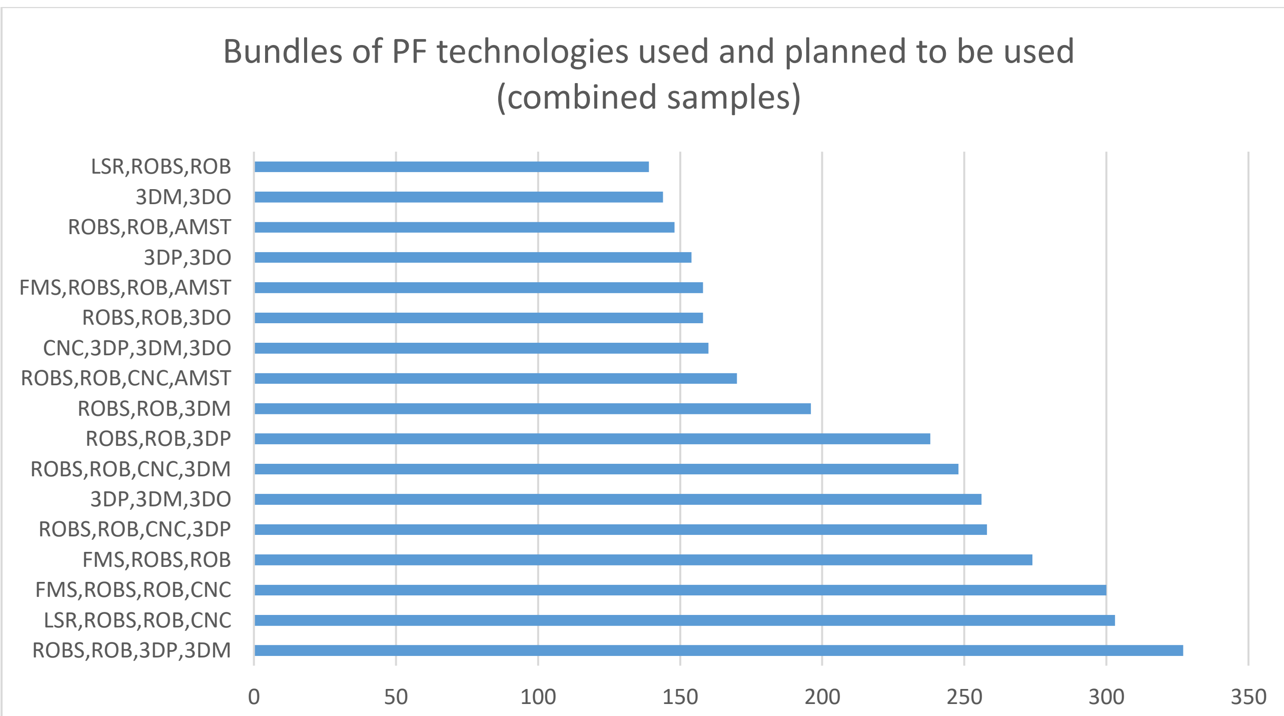

Figure 6.22: Bundles of PF technologies in use and planned to be used (combined samples)

Emerging technology adoption in 2017

The Survey of Innovation and Business Strategy (SIBS) 2017 provides a snapshot about the adoption rate of some emerging technologies, such as the Artificial Intelligence (AI) and Internet of Things (IoT). Table 6.24 displays information about the emerging technologies that required BI in 2017. As was previously mentioned, AI is not expected to have a lot of adoption because BDS was not highly adopted (only 24.6% of firms that have adopted BI technologies were using it in 2014). BI should not be dependent on the sector because all companies require insights from their data. Considering that BI technologies were adopted by 2467 firms out of a total of 7912 (31.2%), the actual adoption rate of BDS was 7.7%. Despite seeing an increase in the planned adoption of this software, AI takes time to be implemented once a company starts using a BDS. This is because AI requires enough data collected, which then needs to be structured in the right way. In this case, firms that were planning to adopt in 2016 do not have enough time to get ready to implement AI in 2017. This certainly justifies, in part, the low adoption rate of AI across all industries (4.0%). However, the reader should note that BDS becomes a necessity only when there is a large volume of data, which is more probable in larger firms. Therefore, the low of adoption of BDS is not the sole reason for the low adoption of AI in 2017. In contrast, the adoption of IoT requires two main components: a BDS to collect and store the data and RFID devices (and sensors) that will gather the data that needs to be stored in a BDS. Assuming companies that were planning to adopt BDS adopted it and used it in 2016, it gives them enough time to start collecting the data from their connected devices. This is why IoT was used more widely than AI in 2017, considering an adoption rate of 12.2%. The adoption of RFID was quite low in 2014 (around 8.8%; refer to Figure 6.1 that was previously discussed). However, there are other technologies that allow to collect data, namely sensors (WSN) and robots with vision or sensors systems (ROBS) as well. Both of these technologies were previously mentioned and had a higher adoption rate when compared to RFID: WSN was adopted by 16.4% of firms, while ROBS was adopted by 24.5% of firms. As a consequence, it can justify why IoT has an adoption rate of 12.2% despite a low adoption rate of RFID. Furthermore, RTM is another technology that could be tied to connected objects because it enables real-time data to be monitored in order to provide managers with insights that can allow them to do quick decision-making. RTM was a technology that was present in many bundles that were planning to be adopted, which could also have contributed to increasing the use of IoT in 2017.

Table 6.24: Adoption of emerging technologies requiring BI in 2017 in Quebec and in Canada

code[a]	Sectors	Total	Size[b] S	M	L	Province/Region Atl.	Qc	On	RoC
	Geomatics or geospatial technologies								
	Total all surveyed industries	3.7[A]	3.2[A]	5.3[A]	7.6[A]	2.6[A]	4.4[A]	3.2[A]	4.0[A]
11	Agriculture, forestry, fishing and hunting	5.3[A]	4.8[A]	11.0[B]	5.2[A]	2.4[A]	11.7[B]	0.0[E]	6.6[B]
21	Mining, quarrying, and oil and gas extraction	11.4[A]	10.3[A]	8.7[A]	18.7[A]	3.4[A]	1.7[A]	10.5[A]	13.1[A]
22	Utilities	18.2[B]	12.6[B]	13.3[B]	35.8[B]	0.0[E]	16.6[B]	20.4[B]	18.0[B]
23	Construction	3.8[A]	3.2[A]	5.8[B]	13.8[A]	1.5[A]	3.6[A]	2.8[A]	5.1[B]
31-33	Manufacturing	1.4[A]	1.1[A]	0.9[A]	4.9[A]	3.2[A]	1.8[A]	1.1[A]	1.0[A]
4x-5x	Total selected services[c]	4.0[A]	3.5[A]	6.3[A]	6.9[A]	2.8[A]	5.0[A]	3.9[A]	3.5[A]
41	Wholesale trade	3.0[A]	2.7[A]	4.7[A]	3.9[A]	1.3[A]	2.8[A]	3.1[A]	3.2[A]
44-45	Retail trade	0.1[A]	0.0[E]	0.7[A]	2.1[A]	0.8[A]	0.1[A]	0.1[A]	0.0[E]
48-49	Transportation and warehousing	4.2[A]	3.3[A]	9.9[A]	9.8[A]	4.7[A]	7.0[A]	4.8[A]	1.7[A]
51	Information and cultural industries	5.8[A]	5.7[A]	6.1[A]	6.0[A]	13.0[B]	4.5[A]	6.2[A]	5.3[B]
52[d]	Finance and insurance excluding monetary authorities 18	13.1[A]	11.3[A]	22.1[A]	12.4[A]	2.9[A]	42.5[A]	2.7[A]	0.9[A]
53	Real estate and rental and leasing	2.6[A]	2.1[A]	3.4[A]	11.7[A]	3.7[A]	9.0[B]	1.0[A]	0.2[A]
54	Professional, scientific and technical services	10.2[A]	9.7[A]	12.8[A]	14.8[A]	6.3[B]	8.6[B]	9.5[A]	13.0[B]
55	Management of companies and enterprises	1.6[A]	1.3[A]	0.0[E]	6.6[A]	0.0[E]	0.0[E]	4.0[B]	0.9[A]
56	Administrative and support, waste management and remediation services	4.7[A]	4.7[B]	6.0[B]	2.7[A]	5.3[B]	0.2[A]	6.5[B]	5.4[B]
	Artificial intelligence (AI)								
	Total all surveyed industries	4.0[A]	3.2[A]	7.1[A]	10.1[A]	3.2[A]	5.4[A]	4.8[A]	2.0[A]
11	Agriculture, forestry, fishing and hunting	1.8[A]	1.6[A]	3.2[A]	2.9[A]	5.0[B]	4.6[B]	0.2[A]	0.7[A]
21	Mining, quarrying, and oil and gas extraction	3.7[A]	1.8[A]	4.9[A]	11.3[A]	3.3[A]	0.0[E]	4.0[A]	4.1[A]
22	Utilities	3.4[A]	0.0[E]	0.0[E]	14.2[B]	0.0[E]	16.6[B]	1.6[A]	2.7[A]
23	Construction	0.8[A]	0.5[A]	3.4[A]	3.2[A]	1.5[A]	2.6[A]	0.5[A]	0.1[A]
31-33	Manufacturing	2.8[A]	2.0[A]	4.5[A]	6.7[A]	1.3[A]	3.4[A]	2.8[A]	2.3[A]
4x-5x	Total selected services[c]	5.3[A]	4.3[A]	9.0[A]	12.7[A]	3.9[A]	6.7[A]	6.6[A]	2.6[A]
41	Wholesale trade	3.0[A]	2.8[A]	2.3[A]	7.1[A]	1.4[A]	2.3[A]	4.3[A]	1.7[A]
44-45	Retail trade	2.1[A]	1.6[A]	6.0[A]	3.9[A]	4.7[B]	2.1[A]	2.8[A]	0.7[A]
48-49	Transportation and warehousing	1.6[A]	1.1[A]	3.8[A]	6.0[A]	3.9[A]	0.5[A]	2.8[A]	1.0[A]
51	Information and cultural industries	16.8[A]	16.1[A]	14.7[A]	25.5[B]	22.3[B]	19.2[A]	19.4[A]	8.6[B]
52[d]	Finance and insurance excluding monetary authorities 18	19.1[A]	15.6[A]	26.4[A]	32.2[A]	4.1[A]	46.0[B]	10.5[A]	7.4[B]
53	Real estate and rental and leasing	2.1[A]	1.9[A]	3.4[A]	5.1[A]	0.0[E]	3.6[B]	3.1[A]	0.2[A]
54	Professional, scientific and technical services	11.5[A]	10.4[A]	14.7[A]	23.6[A]	6.5[B]	9.6[B]	15.7[B]	7.7[B]
55	Management of companies and enterprises	3.2[A]	2.1[A]	0.0[E]	16.4[B]	0.0[E]	7.1[B]	3.8[A]	0.9[A]
56	Administrative and support, waste management and remediation services	4.7[A]	3.2[A]	13.2[B]	6.8[A]	0.0[E]	8.6[B]	5.2[B]	1.9[A]
	Integrated Internet of Things (IoT) systems								
	Total all surveyed industries	12.2[A]	11.4[A]	15.6[A]	17.8[A]	8.6[A]	14.3[A]	13.8[A]	9.3[A]
11	Agriculture, forestry, fishing and hunting	13.8[B]	13.8[B]	13.7[B]	16.4[B]	2.5[A]	4.6[B]	18.9[B]	17.6[E]
21	Mining, quarrying, and oil and gas extraction	11.1[A]	8.7[A]	12.6[A]	20.8[A]	6.8[B]	7.6[A]	11.1[A]	11.8[A]
22	Utilities	18.8[A]	7.7[B]	26.4[B]	44.8[B]	25.8[E]	16.6[B]	24.8[B]	7.9[A]
23	Construction	16.0[B]	16.5[B]	10.5[B]	17.5[A]	8.0[B]	20.0[B]	11.9[B]	18.7[E]
31-33	Manufacturing	9.6[A]	7.4[A]	16.1[A]	18.7[A]	8.8[A]	11.5[A]	10.8[A]	5.2[A]
4x-5x	Total selected services[c]	12.0[A]	11.1[A]	16.7[A]	16.7[A]	9.3[A]	14.6[A]	14.8[A]	6.6[A]
41	Wholesale trade	13.1[A]	12.7[A]	13.5[A]	18.2[A]	6.9[A]	12.7[A]	17.2[A]	8.1[B]
44-45	Retail trade	7.8[A]	7.8[A]	8.0[A]	7.2[A]	7.7[B]	11.4[B]	9.0[B]	3.0[A]
48-49	Transportation and warehousing	11.7[A]	10.2[A]	19.3[A]	21.9[A]	12.5[A]	14.4[B]	14.9[B]	6.9[B]
51	Information and cultural industries	21.3[A]	20.0[A]	28.2[A]	23.3[B]	26.8[B]	17.9[A]	24.5[A]	18.7[B]
52[d]	Finance and insurance excluding monetary authorities 18	20.6[A]	18.9[A]	30.8[A]	17.8[A]	13.4[A]	43.8[A]	14.2[A]	8.0[A]
53	Real estate and rental and leasing	6.3[B]	5.6[B]	7.0[B]	18.0[A]	0.0[E]	0.3[A]	9.6[B]	6.6[B]
54	Professional, scientific and technical services	17.0[A]	15.2[A]	27.2[B]	28.0[A]	12.0[B]	21.1[B]	18.1[B]	13.1[B]
55	Management of companies and enterprises	6.3[A]	4.0[A]	10.2[B]	19.8[B]	9.0[B]	11.0[B]	5.8[A]	3.3[A]
56	Administrative and support, waste management and remediation services	12.5[B]	11.5[B]	20.7[B]	10.0[A]	11.4[B]	11.1[B]	20.1[B]	3.4[A]

Notes : Source : Statistics Canada, Survey of Innovation and Business Strategy 2017 : table 27-10-0155-01– Introduction of different types of innovation by industry and enterprise size : https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=2710015501

[a] NAICS codes (2012);

[b] Size: S: Small enterprises (20 to 99 employees), M: Medium enterprises (100 to 249 employees), L: Large enterprises (250 employees and more);

[c] This sector grouping includes the following NAICS codes: 41, 44-45, 48-49, 51, 52, 53, 54, 55 and 56;

[d] This category excludes NAICS code 521;

[A, B, E] Data quality: excellent (A), very good (B), use with caution (E).

6.6 Summary and conclusions

The results demonstrated the different complementarities between each category of technologies: Material Handling, Supply Chain and Logistics (MHSCL), Business Intelligence (BI), Design and Information Control (DIC), and Processing and Fabrication (PF). Regarding the MHSCL family, it was anticipated that the different technologies adopted will resemble the following pattern:

$$\{CRM, TMS, WMS\} + \{SCCVS, DF/DP\} + \{QR/RFID, AS/RS\}$$

The three most popular bundles sorted by confidence and support respectively are displayed in Table 6.25. Analyzing the rules with the highest confidence rate shows that, only two of the three expected types of technologies are adopted. There are software tools, planning and collaboration tools but no tracking tools. This suggests that QR and RFID technologies are not part of the core technologies that firms adopt. Despite QR being widespread, it seems that firms are split between adopting QR, RFID and AS/RS, hence the reason why these technologies are not included the rules displayed. Because the confidence and support thresholds were respectively set to 0.8 and 0.05 initially, many other possible rules were not generated. In fact, lowering these thresholds yielded more results regarding the tracking technologies. As was previously mentioned, some rules with lower thresholds generated these technologies (e.g. Table 6.5, Table 6.6, Table 6.7). Analyzing the most frequently adopted MHSCL bundles of technologies suggests that the initial proposition with regards to the patterns of adopted technologies made sense, despite not having many bundles in the top 15 having QR, RFID and AS/RS.

Table 6.25: Top 3 MHSCL bundles sorted by confidence and support

	LHS		RHS	Support	Confidence	Lift	Count
C1	{CRM, DF, SCCVS, TMS}	=>	{WMS}	0.053	0.866	1.964	187
C2	{CRM, SCCVS, TMS, WMS}	=>	{DF}	0.053	0.862	2.375	187
C3	{DF, SCCVS, TMS}	=>	{WMS}	0.068	0.841	1.907	238
S1	{SCCVS}	=>	{WMS}	0.168	0.692	1.571	590
S2	{SCCVS}	=>	{DF}	0.146	0.602	1.660	513
S3	{CRM, DF}	=>	{WMS}	0.121	0.603	1.367	425

Table 6.26 shows the top three BI rules sorted by confidence and support, respectively. Analyzing these rules highlights the importance of SaaS technology. Regardless of what other BI technologies were adopted, it appears that SaaS was always part of larger bundles. This result was expected because of how inexpensive SaaS can be compared to traditional software. Firms do not need to have large IT teams that will be install and maintain a software. This is done through the service provider of a cloud software. The rules sorted by support exhibit a similar story considering two of them include SaaS. These two rules have the same support because they involve the same technologies. However, there is a large gap between the confidence of both rules. A high difference in confidence may be used to derive a casual hypothesis that one technology leads to another but not the other way around (Merceron & Yacef, 2003). In this context, IaaS leads to SaaS but not the other way around. Security is the number one concern firms face when adopting cloud computing (Bannerman, 2010). Generally, SaaS provides the most security because it only stores data related to software use while IaaS puts the responsibility of assuming security on the customer (Brunette & Mogull, 2009). If firms already trust the IaaS process, it will be much easier for them to also adopt SaaS because the big security risk is already taken into consideration. The other way is less true, as seen with these two rules.

Table 6.26: Top BI rules sorted by confidence and support

	LHS		RHS	Support	Confidence	Lift	Count
C1	{BDS,ED,IaaS,RTM}	=>	{SaaS}	0.053	0.977	1.897	130
C2	{BDS,ED,IaaS}	=>	{SaaS}	0.063	0.951	1.846	156
C3	{BDS,IaaS,RTM}	=>	{SaaS}	0.066	0.942	1.828	162
S1	{IaaS}	=>	{SaaS}	0.273	0.841	1.633	674
S2	{SaaS}	=>	{IaaS}	0.273	0.530	1.633	674
S3	{BDS}	=>	{ED}	0.146	0.593	1.164	360

Table 6.27 shows the bundles of DIC technologies that were the most frequently adopted. Whether analyzing rules by confidence or by support, the adoption pattern that was proposed does not seem to be what firms are using.

{VPD, VM} + {ERP, MRPII, MES, CIM} + {WSN, EDI, WCP} + {UAS, ASI}

With the exception of EDI that appeared to be included in many bundles, there were no other technologies with regards to communication tools (e.g. WSN, EDI, WCP) and inspection systems (e.g. UAS, ASI). For instance, ASI appeared in rules with a confidence of 1 (e.g.

Table 6.17), which highlights the small number of firms having adopted specific bundles of technologies that included ASI. Furthermore, EDI was the most frequently adopted technology and this is justified by the importance of sharing design files internally or externally with partners. While it may seem that this technology did not have many complementarities, the findings suggest that it was mostly adopted with design and integration tools (i.e. VPD, VM; ERP, MRPII, MES and CIM). Both groups of technologies require secure transfer of files and data, thus justifying the high adoption rate of EDI. However, most bundles include a design tool, as well as an integration tool, which is expected considering the design and integration technologies were the most frequently adopted. Amongst the top four technologies adopted, two are communication tools (WCP and EDI), one is a design tool (CAX) and one is an integration tool (ERP). These technologies follow the pattern that was expected to be found, with the exception of UAS and ASI technologies. These inspection tools are highly advanced technologies that use machine learning to enhance image processing, thus making them expensive. Unsurprisingly, both technologies have lower adoption rate: 20% for ASI and less than 5% for UAS. As was previously mentioned, AI was expected to have a low adoption rate, which was also confirmed with SIB 2017 in Table 6.24. As a consequence, firms may have been less inclined to adopt solutions based on machine learning.

Table 6.27: Top 3 DIC bundles sorted by confidence and support

	LHS		RHS	Support	Confidence	Lift	Count
C1	{ERP, VM}	=>	{CAX}	0.053	0.899	1.824	204
C2	{VM}	=>	{CAX}	0.091	0.884	1.793	349
C3	{EDI, VM}	=>	{CAX}	0.052	0.883	1.793	197
S1	{MRPII}	=>	{ERP}	0.154	0.734	1.710	586
S2	{ERP, WCP}	=>	{EDI}	0.119	0.713	1.350	455
S3	{EDI, MRPII}	=>	{ERP}	0.099	0.749	1.743	378

Table 6.28 shows the most frequently adopted bundles of PF technologies sorted by confidence and support respectively. The proposition was to find the following pattern amongst the rules generated by the *apriori* algorithm:

{CNC, FMS/FMC} + {AMST, ROBOT(s)} + {PS, MM, MEMS, LSR, 3DP/3DM/3DO}

The top three rules by confidence suggest this pattern is what was considered by firms when adopting PF technologies. The rules C2 and C3 comprise the use of CNC, ROB combined with two different technologies, either 3D printing or lasers used in material processing (LSR) which are considered as advanced techniques of manufacturing. There is a similar pattern when analyzing the top three rules by support. It should be noted that the core manufacturing technologies involve the first two categories, namely machinery control (e.g. CNC, FMS/FMC) and inspection/transportation of materials (e.g. AMST, ROB, ROBS). Both of these categories can be considered the minimum requirements to run manufacturing activities. The last category includes all the advanced manufacturing technologies amongst which 3D printing and lasers seem to be the most promising. Compared to all technologies in the third category, LSR and 3DP (3D printing for plastics) have the highest adoption rates, which is why they have a presence in the rules generated. The other advanced techniques have an adoption rate that is lower than 5%, suggesting that only early adopters could be using them. The results also highlight that 2014 could have been the start of the fourth Industrial Revolution in Canada. Despite the low adoption rates of technologies such as MEMS and MM, there has been a growing interest amongst firms to adopt 3D printing technologies (especially for plastics) as well as lasers for material processing, suggesting the desire for firms to go towards more advanced technologies.

Table 6.28: Top 3 PF bundles sorted by confidence and support

ID	LHS		RHS	Support	Confidence	Lift	Count
C1	{3DM,3DO}	=>	{3DP}	0.032	0.923	5.197	48
C2	{3DP, LSR, ROB}	=>	{CNC}	0.027	0.891	1.861	41
C3	{3DO, ROB}	=>	{CNC}	0.026	0.886	1.851	39
S1	{CNC, ROBS}	=>	{ROB}	0.077	0.688	2.583	117
S2	{LSR, ROB}	=>	{CNC}	0.062	0.772	1.613	95
S3	{3DM}	=>	{3DP}	0.055	0.748	4.210	83

Furthermore, briefly exploring the rules generated for firms planning to adopt technologies between 2014 and 2016, there is an important increase in the number of bundles containing 3D printing technologies (see Figure 6.21, Figure 6.22). However, this is not the case for other advanced techniques such as PS, MM or MEMS, which suggest the highly specialized nature of these activities. It should be noted that many firms manufacturing at large-scale are located in South-East Asia, which can explain the low adoption rate in Canada. It is possible that the COVID-19 pandemic could have brought back some of these manufacturing activities to Canada.

This study explored a new methodology to understand the different types of technologies adopted by firms in Canada. As was previously mentioned, the algorithm used provides the ability to bridging the gap between macro and micro levels (Aguinis et al., 2013), specifically between academics and practitioners (Cascio & Aguinis, 2008). This data-mining technique was used to explore practical implications of customer behaviours (Berry & Linoff, 2004). In this case, the customers are the enterprises buying and adopting these advanced technologies. The analysis provided important insights as to which technologies are complementary, thus reinforcing the definition of technological proximity provided in the literature review. It should be noted that the results not only provided frequently adopted rules, but also strong rules displaying proximity and best practices in technology adoption behaviours. Furthermore, there were many similar bundles that were differentiated by a few technologies. This suggests that there are core technologies that are essential to a firm's core activities in addition to "à la carte" technologies that can be adapted based what a firm really needs. While proximity within technologies can enable firms to interact more efficiently, technological distance grants the possibility to combine different types of knowledge (Nooteboom, Van Haverbeke, Duysters, Gilsing, & Van den Oord, 2007). According to Schamp, Rentmeister, and Lo (2004), technological proximity is a virtual concept that refers to homogeneity between actors in terms of technological knowledge bases (Liang & Liu, 2018). Companies will tend to adopt technologies based on external pressure. The goal of having a good balance of technological proximity is to be able to access new technologies adopted by other actors (Van de Vrande, 2013).

However, it can be argued that technological proximity does not only apply to firms and their partners, but to the different technologies as well. Similar to the fact that firms wanting to adopt a new technology require absorptive capacity (W. M. Cohen & Levinthal, 1990), new advanced technologies need to be able to have a certain complementarity to be able to communicate together. In a world of connected objects, robots and artificial intelligence, it is imperative that people learn how to work with robots as well as robots need to learn to work with other robots as well. This is an important concept to add even though it could not be measured with the data at hand in this thesis. However, it would be important for firms to target their technology strategy around how close technology needs to be with humans and other technology as well.

In terms of limitation of this study, there are a few that are worth mentioning. First, no industry analysis was made because of low samples in the survey. The support level was relatively low for most technologies, the maximum being around 15%. If the sample was divided in different sectors, the support level would have been even lower. One way will be to group technologies according to the propositions made in each category so that it includes 4 or 5 technologies instead of 8 or 12, for example. This will increase the sample size of technologies and an industry analysis becomes pertinent. Second, because the support levels are low, it is difficult to conclude what would be the optimal bundles to adopt based on a firm's core activities. This is a consequence of the overall sample that is small. This can also be explained by the fact that firms adopt technologies to solve specific business problems. Because this is information was not available, it is not possible to understand if there is such a thing as an optimal bundle to solve a specific problem.

Furthermore, the low adoption rate in certain categories of technologies, specifically the PF category are another reason for low support values. One way to see a higher adoption rate would be to have another data set more recent data, which would make it possible to compare before and after Industry 4.0. However, these types of surveys are not always available and this might not be the best course of action. It can be quite costly to administer another similar survey with more than 8000 targeted firms.

CHAPTER 7 FREQUENT SEQUENCE MINING (TEMPORAL RULES)

This section uses the same data as the previous chapter but with the added information pertaining to the time of adoption of each technology. As was previously mentioned, firms could choose between three categories with regards to when they have adopted a technology: (1) three years or more; (2) three years or less; (3) planning to adopt within three years. While the previous analysis only considered adopters of technology (categories 1 and 2 recoded as 1), this methodology does not recode the initial data. This provides three temporal data points to be used in the *cspade* algorithm, which will mine the frequent sequential item sets. In the previous chapter, the analysis considered each family of technologies separately because there were enough firms that had adopted each family. However, because of the small samples in the adoption of different technologies, the results are only presented while considering all categories of technologies in the same analysis. In this analysis, all families of technologies are combined, which will provide insight into the sequential patterns followed by firms when they decide to acquire new technologies. The chapter is divided into three sections related to the association rules generated with the *cspade* algorithm. First, rules that predict the adoption of a BI technology will be presented. Then, rules predicting the adoption of 3D printing technologies will be explored further. Finally, a summary and recommendations section will be presented based on these results and the ones from the previous chapter.

7.1 Frequent sequential rules predicting a BI technology

Contrary to the interpretation of the previous association rules in Chapter 6, the left-hand side (LHS) represents the technologies that were adopted previously by firms while the right-hand side (RHS) considers the technologies that are planned to be adopted in the future. In other words, there is a sequential component to the rule. The first step of the analysis consisted in sorting rules by support and confidence. However, lift values are generally much lower when the temporality is added: most rules have a lift value close to 1, which indicates that the LHS and the RHS are independent. Because the lift is a measure of correlation, sorting the rules by lift was the preferred method in this case. The top 18 rules (sorted by lift) predicting the adoption of BI technologies can be found in Table 7.1. In this case, some rules have more than one technology in the consequence, which means that both of these technologies are adopted at the same time, but sometime after the adoption of technologies shown in the antecedent. For instance, L1.1 shows that firms who adopted ERP, QR and EDI around the same time (either for more than three years or for three years or less), also purchased technologies ED and IaaS together at a later time. This first rule is pertinent because it could mean that logistics suppliers have adopted core technologies for their business to function and then decided to adopt BI tools. The adoption of ED suggests the need to summarize data in dashboards to guide executives with decision-making, while IaaS underlines a shift towards storing company data in the cloud. The rest of the rules show the adoption of IaaS as a consequent, which highlights firms' desire to move towards cloud computing. A confidence around 33% for most of these rules suggests that 1 out of 3 firms has planned to adopt IaaS sometime in the future, after they have adopted their core technologies, whether in the MHSCL, DIC or PF families. The result of having a high number of firms wanting to adopt IaaS is definitely interesting and shows how important this technology is. Due to its flexibility and relatively low cost compared to traditional data servers, it is no surprise that many companies are adopting it after they have purchased the core technologies needed to run their business. This being said, this is the picture that was available in 2014 and it could be argued the confidence of adopting IaaS would have been higher if survey had been done more recently. Cloud computing continued to gain popularity along the years and many new IaaS or SaaS companies are entering the market.

However, one important technology that was not visible in this analysis is BDS. As was previously highlighted many times in this thesis, large firms or companies with a lot of data require a BDS to fully profit from AI adoption. While it can be complicated for companies to implement it, many of them were still planning on adopting it in the future. To view the rules related to BDS, one has to look at lift values that are lower than what is already displayed in Table 7.1.

Table 7.1: Temporal rules predicting adoption of BI technologies sorted by lift

ID	LHS		RHS	Support	Confidence	Lift
L1.1	{ERP, QR, EDI}	=>	{ED, IaaS}	0.01	0.15	1.39
L1.2	{WMS, ERP, QR, EDI, WCP}	=>	{IaaS}	0.01	0.37	1.35
L1.3	{TMS, WMS, EDI, WCP}	=>	{IaaS}	0.01	0.35	1.31
L1.4	{ERP, QR, EDI, WCP}	=>	{IaaS}	0.01	0.35	1.30
L1.5	{WMS, ERP, EDI}	=>	{ED, IaaS}	0.01	0.14	1.30
L1.6	{WMS, QR, EDI, WCP}	=>	{IaaS}	0.01	0.35	1.29
L1.7	{WMS, EDI, WSN}	=>	{IaaS}	0.01	0.35	1.28
L1.8	{CAX, ERP, QR, EDI}	=>	{IaaS}	0.01	0.34	1.26
L1.9	{WMS, EDI, WCP}	=>	{IaaS}	0.02	0.33	1.23
L1.10	{WMS, ERP, EDI, WCP}	=>	{IaaS}	0.01	0.33	1.22
L1.11	{TMS, EDI, WCP}	=>	{IaaS}	0.01	0.33	1.22
L1.12	{DF, WMS, EDI, WCP}	=>	{IaaS}	0.01	0.33	1.20
L1.13	{WMS, QR, EDI, WCP}	=>	{SaaS, IaaS}	0.01	0.24	1.19
L1.14	{WMS, ERP, QR, EDI}	=>	{IaaS}	0.02	0.32	1.17
L1.15	{WMS, ERP, QR, WCP}	=>	{IaaS}	0.01	0.31	1.16
L1.16	{WMS, ERP, QR}	=>	{ED, IaaS}	0.01	0.12	1.15
L1.17	{WMS, EDI, WCP}	=>	{SaaS, IaaS}	0.01	0.23	1.15
L1.18	{TMS, WMS, WCP}	=>	{IaaS}	0.01	0.31	1.14

In general, most RTM software will require a BDS such as Hadoop. While having adopted an RTM does not automatically mean that there is a big data software behind it, there is a high chance in practice that this is the case. In this case, there is a chance that firms have only adopted an RTM without mentioning that they have also adopted a BDS since the only example of BDS provided in the survey was Hadoop. Table 7.2 shows a few selected temporal rules that predicted the adoption of BDS and RTM. The table highlights two sets of rules: those that have a lift higher than 1 and those that have a lift lower than 1. Lift values higher than 1 mean that the adoption of antecedent technology increases the chances of adopting the consequent technology in the future. On the other hand, a lift value lower than one suggests that the antecedent decreases the probability of adopting the consequent.

Table 7.2: Temporal rules predicting BDS and RTM (sorted by lift)

ID	LHS		RHS	Support	Confidence	Lift
L2.1	{ERP, EDI, WCP}	=>	{BDS}	0.01	0.20	1.14
L2.2	{QR, EDI, WCP}	=>	{BDS}	0.01	0.18	1.05
L2.3	{ERP, QR, EDI}	=>	{BDS}	0.01	0.18	1.05
L2.4	{ERP, QR, WCP}	=>	{BDS}	0.01	0.18	1.04
L2.5	{WMS, EDI, WCP}	=>	{BDS}	0.01	0.18	1.04
L2.6	{CAX, ERP, QR, EDI}	=>	{RTM}	0.01	0.32	1.04
L2.7	{ERP, QR, EDI, WCP}	=>	{RTM}	0.01	0.32	1.03
L2.8	{EDI, WSN}	=>	{BDS}	0.01	0.18	1.03
L2.9	{MES}	=>	{RTM}	0.02	0.15	0.49
L2.10	{VM}	=>	{RTM}	0.01	0.15	0.49
L2.11	{MRPII}	=>	{RTM}	0.03	0.14	0.47
L2.12	{CRM}	=>	{RTM}	0.06	0.14	0.45
L2.13	{SI}	=>	{RTM}	0.03	0.13	0.41
L2.14	{ED, EDI}	=>	{RTM}	0.01	0.11	0.37
L2.15	{CRM, IaaS}	=>	{RTM}	0.01	0.11	0.35
L2.16	{BDS}	=>	{RTM}	0.02	0.10	0.33

Most of the rules in Table 7.2 have a lift that is very near 1, which suggests an independence of both the antecedent technology. As was found in the previous chapter, the sample of firms that have adopted a large-scale data processing software was low: BDS was the least adopted technology in the BI family. Despite having seen that some companies planned to adopt it in the future, the rules clearly highlight that there is no clear pattern that will greatly increase the probability of BDS to be adopted. The first rule in Table 7.2 (i.e. L2.1) has a lift value of 1.14, which means that the technologies in LHS (i.e. ERP, EDI, WCP) increases the probability of adopting a BDS by 14%. However, the confidence is still quite low: 1 out of 5 firms will adopt this technology in the future. Companies who are using ERP, EDI and WCP might be larger companies that should have enough capital to justify a BDS adoption, but this is not the case for a large sample of the survey. As was previously mentioned, it is no surprise that AI adoption was low in 2017 in

Canada (refer to Table 6.24). Referring to the rules in Table 7.2, one can notice L2.16 which has the lowest lift out of all rules. The presence of BDS decreases the probability of adopting RTM at a later stage, which suggests that RTM could be seen as a substitute technology for firms having adopted a large-scale data processing software. It makes sense from a practical perspective because most BDS will include some form of real-time monitoring, making both technologies intertwined. While this assumption is not to be taken lightly, the *cspade* algorithm was run a second time by considering RTM and BDS as the same technology (i.e. BDS and RTM both recoded to BDS/RTM). This manipulation provided new rules with a higher confidence rate. They can be found in Table 7.3. It should be noted that all rules had a minimum of four technologies adopted before they wanted to adopt a BDS. This highlights the fact that firms prefer to set up their main business activities first before having enough data that can be collected and managed a BDS/RTM. It can also mean that only larger firms or those with more capital can invest into many technologies and a BDS. Clearly, companies prefer to focus on their BI needs at a later point. Despite having a higher confidence (40%), these rules still need to be interpreted with caution because all of the lift values are very close to 1. The results are in line with the findings of the previous chapter. Firms were definitely planning to adopt the advanced technologies that can lead to AI implementation, but there is still a long way to go before AI adoption can reach a high in Canada.

Table 7.3: Temporal rules predicting the adoption of BDS/RTM (sorted by lift)

ID	LHS		RHS	Support	Confidence	Lift
L3.1	{EDI, ERP, QR, CAX}	=>	{BDS/RTM}	0.013	0.407	1.137
L3.2	{EDI, ERP, WCP, ASI}	=>	{BDS/RTM}	0.010	0.405	1.132
L3.3	{EDI, ERP, QR, WCP}	=>	{BDS/RTM}	0.016	0.405	1.132
L3.4	{ERP, QR, WCP, CAX}	=>	{BDS/RTM}	0.010	0.401	1.121
L3.5	{EDI, ERP, QR, WCP, WMS}	=>	{BDS/RTM}	0.011	0.395	1.104

7.2 Frequent sequential rules predicting 3D printing technologies

Table 7.4 shows the top 15 rules sorted by lift value that involved a 3D printing technology. The first important aspect is that all of the rules indicated that companies purchased 3DM technologies after adopting technologies from different families (i.e. MHSCL, DIC and PF). The confidence measures are very low compared the previous analysis with the *apriori* algorithm. This is mainly due to the fact that the sample of firms is smaller when considering the time of adoption. When separating the sample into three distinct timestamps, there are certainly fewer firms in each category. As a consequence, the support is also low. However, by grouping some of these similar rules, it is possible to increase the confidence of some rules.

Table 7.4: Temporal rules predicting the adoption of 3D printing (sorted by lift)

ID	LHS		RHS	Support	Confidence	Lift
L4.1	{CAX, CNC}	=>	{3DM}	0.013	0.163	3.176
L4.2	{CNC, ERP}	=>	{3DP}	0.010	0.196	2.642
L4.3	{CAX, MRPII}	=>	{3DM}	0.010	0.134	2.613
L4.4	{CNC}	=>	{3DM}	0.018	0.126	2.459
L4.5	{CAX, ERP}	=>	{3DM}	0.016	0.122	2.373
L4.6	{CAX, CNC}	=>	{3DP}	0.014	0.172	2.311
L4.7	{CAX, ERP, EDI}	=>	{3DP}	0.010	0.155	2.088
L4.8	{CAX, MRPII}	=>	{3DP}	0.011	0.150	2.018
L4.9	{CAX, EDI}	=>	{3DM}	0.013	0.102	1.992
L4.10	{CAX, ERP}	=>	{3DP}	0.017	0.135	1.818
L4.11	{ROB}	=>	{3DP}	0.012	0.132	1.784
L4.12	{CNC}	=>	{3DP}	0.019	0.131	1.763
L4.13	{CAX, QR}	=>	{3DP}	0.010	0.126	1.690
L4.14	{CAX, EDI}	=>	{3DP}	0.015	0.124	1.672
L4.15	{CAX, WMS}	=>	{3DP}	0.010	0.124	1.663

For instance, L4.1 and L4.6 can be grouped: if a company has adopted CAX and CNC at a previous time, it has a probability of 16.3% and 17.3% to adopt 3DM and 3DP at a later stage, respectively.

While these confidence levels might seem low compared to what was found with the *aprori* algorithm previously, there is still some important facts to mention. By analyzing the lift values of these rules, the antecedent technologies highly increased the confidence of a firm to adopt 3D printing technologies (lift values of 3.18 and 2.31 respectively). Considering that additive manufacturing requires the same type of technologies that is adapted to be used with different materials, another analysis would consist in regrouping the 3D printing technologies into one category (i.e. recoding 3DP, 3DM and 3DO to 3D). By doing this recoding, the sample size of a general adoption of 3D printing will increase, which should increase the confidence levels as well. The new generated rules can be found in Table 7.5. Rule L2.5 is obtained by combining rules L5.1 and L5.6 from the previous table, which now shows that adopting a CAX and CNC together increased the probability of adopting 3D printing to 24.6%.

Table 7.5: Temporal rules predicting the adoption of any type of 3D printing (sorted by lift)

ID	**LHS**		**RHS**	**Support**	**Confidence**	**Lift**
L5.1	{ERP, CAX, CNC}	=>	{3D}	0.012	0.321	3.427
L5.2	{ERP, CNC}	=>	{3D}	0.015	0.278	2.969
L5.3	{MRPII, CNC}	=>	{3D}	0.010	0.262	2.791
L5.4	{EDI, CNC}	=>	{3D}	0.012	0.259	2.764
L5.5	{CAX, CNC}	=>	{3D}	0.020	0.246	2.620

Furthermore, rule L5.1 is new and was not part of the previous generated rules. L5.1 has the highest lift value (3.427) and the highest confidence level (32.1%), suggesting that 1 out of 3 firms adopted 3D printing after having adopted ERP, CAX and CNC at the same time.

All the other rules have CNC as an antecedent technology and provide over 25% confidence rate for additive manufacturing adoption. This confirms what was previously mentioned considering that many firms were planning to adopt 3D printing technologies (e.g. see Figure 6.22). While this result was expected, the novelty here is that technologies that were adopted before 3D printing are known. Amongst these, CNC and CAX make complete sense from a practical standpoint. Manufacturing companies adopt in many cases 3D printing for rapid prototyping or manufacturing highly customizable products. Regardless of the expected purpose of these technologies, a CNC is a core machinery to any manufacturing firm and was definitely the go-to technology before 3D printing started to become more popular. Moreover, all lift values are greater than 1, which underlines that companies are not replacing CNC, but rather complementing it with 3D printing technologies. While additive manufacturing was getting more attention in the 2000s, it is quite clear that there was an important shift happening with Industry 4.0 where between 25% and 32% having adopted a specific set of technologies were looking to purchase 3D printers.

7.3 Summary and conclusion

The analysis presented in this chapter outlined the advantages and disadvantages of using the *cspade* algorithm when the data includes timestamps as to when a technology has been adopted. The main positive aspect is that it enabled to map on a timeline in which order technologies were adopted. However, the disadvantage is that in presence of low sample size like in SAT 2014, support, confidence and lift can be low because there are not many transactions available. Despite the small sample at disposition, there were a few pertinent outcomes that can be summarized.

First, IaaS technology that was the most likely to be adopted in the future. This can be explained by the fact that companies are starting to see the benefits of using not only a software in the cloud but also to store their data elsewhere. In the static association rules, it was demonstrated that firms are more likely to adopt IaaS if SaaS was already adopted. By adding the temporal element to these association rules, it can be noted that IaaS is always a consequent with confidence rates of over 30%. While this number is rather low compared to the static rules, it shows that firms are starting to direct their efforts into adopting IaaS. With large volume of data constantly that will keep growing over the next few years, companies are starting to realize that they cannot store everything locally, on their own servers.

Second, this thesis showed over the previous chapters that companies may not be ready for AI implementation because they don’t have the required technologies to facilitate its adoption. The analysis in this chapter confirmed this behaviour because based on specific technologies already in use, there was a 12% probability in most cases to adopt a BDS in the future. A similar percentage was found in the case of RTM. As was previously mentioned, RTM usually requires a BDS and by considering both technologies as a single one, the probability of adopting BDS in the future soars to 40%. This was, however, based on a low support of 1% on average, which means that not many firms said that they wanted to adopt this tool. Furthermore, assuming firms adopted a BDS between 2015 and 2017, it still wouldn't be enough time for these firms to be ready to implement AI. As a consequence, this analysis demonstrated that Canadian firms are still far from implementing AI, despite the various initiatives that have been put in place recently to stimulate the use of artificial intelligence (e.g. Scale AI, IVADO). However, it is worth noting that for smaller firms that have fewer data, an ERP or a data warehouse could serve as the main source of data for AI use cases. While this may be true, there was no way to measure this in the survey. While companies may not be ready for AI, some of them could have already adopted it using their database that contains a smaller amount of data. These results are to be taken with a pinch of salt, especially for the smaller companies. Furthermore, it was not possible to measure the amount of data collected by firms, so a BDS adoption may not only be relevant for larger companies. Considering that this technology would only be adopted for large volumes of data, the conclusion that its adoption rate was low still stands. What is certain is that Canadian firms did not adopt a lot of AI in 2017 (only 4% of companies reported using AI, based on the SIBS 2017 survey) but it is not possible to confirm that this is only due to a lower adoption rate of BDS. More research will need to be conducted within that area to understand the causes of a low AI adoption rate.

The same can be concluded for 3D printing technologies. This analysis outlined that approximately 1 out of 3 firms were planning to adopt this technology between 2015 and 2017, but on a very low support of 1% on average. It showed that enterprises are planning to adopt 3D printers in complementarity with CNC, which is the traditional approach to manufacturing. As previously mentioned, the flexibility and cost reduction potential of additive manufacturing are definitely weighing in on companies' decision to add this technology in their portfolio.

Finally, there was no mention of RFID in this chapter because it was not visible in the rules generated. In fact, apart from the few companies that have adopted it, RFID was predicted in one rule, in which the lift was lower than 1. This result demonstrated that very firms had the tendency to plan an RFID adoption.

CHAPTER 8 CONCLUSION (AND RECOMMENDATIONS)

This chapter focusses on reviewing the research questions and the objectives of this research. Then, the contributions to the literature will be presented, followed by practical recommendations. Finally, a section will be dedicated to mentioning the limits of this study and possible follow-up research paths.

8.1 Reviewing research questions, hypotheses and objectives

The first set of questions was aimed at examining the joint impact of OI practices and advanced technology adoption on the propensity to innovate. This question was answered by using an Instrumental-Variable Probit Regression (IVPR) to test five hypotheses. Technology adoption was considered endogenous in this model and was thought to be impacted by three instruments: (1) the number of measures to counter the obstacles to technology adoption; (2) the amount of capital expenditures (CAPEX) in new technologies; (3) a dummy variable about whether or not companies recruiting employees pertaining this said adoption. All the models were correctly specified with the exception of one examining the firms having adopted MHSCL technologies, thus the results for this specific sample need to be interpreted with caution.

The first two hypotheses (H1 and H2) focussed on OI and collaboration practices. Both hypotheses were validated for firms adopting logistics and business intelligence technologies. However, this was not the case for companies that adopted AMTs (i.e. DIC and PF technologies). This sample of firms was concentrated in the manufacturing sector where other business practices seemed to be preferred. The third hypothesis that consisted in studying the impact of cross-functional teams (CFT) was also validated across all technologies. CFT has been focussed on the development of new products (Lopes Pimenta et al., 2014). Creativity is an integral part of this business practice that can result in higher innovation propensity when it comes to product development (Bunduchi, 2009). CFT had a positive and significant coefficient when tested against product innovation and this effect was observed across all technologies. This study also explored the effect of outsourcing, which is validated for BI and MHSCL but not for DIC/PF. DIC/PF interactions with the outside world did not seem to yield a significant effect, which could suggest their propensity to innovate is mostly driven by advanced technologies they use. The last hypothesis is the core of this study that focussed on understanding if the number of advanced technologies had a positive impact on the propensity to innovate, which was validated for all families of technologies and all innovation types. It should also be noted that, in general, manufacturing companies adopting BI technologies were seen as more innovative than service firms. However, high-tech manufacturing firms that adopted PF technologies showed a negative impact on business process innovations when compared to service firms. What is clear from this research is that firms relied on technology to increase their innovation propensity, which in turn should have contributed to increase their innovation performance, although there was no way to measure this in the study.

The second set of questions consisted in exploring the patterns of technology adoption by Canadian firms. The characteristics of the firms adopting certain bundles of interest were to be studied as well. Three propositions were made with regards to the composition of technology bundles that were adopted by firms. These suggestions were an attempt to anticipate the different groups of technologies that companies decided to adopt. While some of these patterns were found in the list of association rules generated, this study arrived at the conclusion that enterprises adopt technologies "à la carte" based on their core activities, but probably based on other determinants such as cost and environmental pressure, which were not the measured in this analysis. However, cost was demonstrated to be an important factor that affects the number of technologies adopted by answering the first set of questions with the IVPR models.

The last set of questions focussed on adding temporal information to the patterns of technology adoption that were discovered in the market basket analysis that was performed previously. The goal was to understand in which order technologies are being adopted by firms. These questions have been answered with specific examples of advanced technologies that show the path firms are taking towards the fourth industrial revolution.

The general objective aimed at investigating the Canadian context of advanced technology adoption was achieved by answering these three sets research questions. Objectives 1 and 2 were fulfilled through the IVPR methodology that was reviewed in Chapter 5 by validating the 5 hypotheses mentioned above. Chapter 6 focussed on portraying the different bundles of technologies that firms have adopted, which contributed to attaining objectives 3 and 4. The *apriori* algorithm was used understand the patterns of technology adoption for the first time in the field of innovation management. A network of technologies was illustrated and firm characteristics were also described with regards to certain popular bundles of technologies adopted. Objectives 5 and 6 were the focus of Chapter 7, which added a temporal element by using the *cspade* algorithm to mine frequent sequences. This method enabled to see in which order technologies were adopted, highlighting pertinent results in terms of BDS and 3D printing adoption, two technologies that are definitely necessary in the shift towards I4.0. Finally, objective 7 consisted in providing business implications. This will be done further below in section 8.3.

8.2 Limits of the study and future research paths

Our results and study had several limits. Before presenting the limits of the study, there is an important point to remind regarding the IVPR model of MHSCL technologies. The results that were described above need to be interpreted with caution because the model was not correctly specified. While there was confirmation of endogeneity, other instruments were tested to try to fix this issue, but the model could never be correctly specified. The other limits are presented below.

First, the reference period of advanced technology adoption and the introduction of innovations is almost the same. There is a possibility that some firms are considering the adoption of a new technology as the introduction of an innovation. Considering that advanced technology may impact the propensity to innovate, this effect is not instant and can take time to show. However, it is not possible to completely dissociate the effect of technology adoption and the introduction of innovation.

Second, the advanced technologies of the survey may have not contained enough information, which would have created a limit in the survey in itself. Some technologies such as EDI and ERP are not manufacturing technologies by definition, but have nonetheless been grouped with other manufacturing technologies in the survey. Firms who adopted these technologies outside the manufacturing sector might be disregarded in this section. Furthermore, the technologies seemed to have been heavily focussed on the manufacturing and resource-intensive sectors. While other industries were also part of the survey, the service industry is not fully represented by the technologies listed. The same can be said for business practices that may help improve innovation propensity, such as collaboration, cross-functional teams and concurrent engineering. These practices are more prominent in the manufacturing sector in general. Furthermore, the classification these technologies might need an update in the future. For BI technologies in particular, including SaaS or IaaS does not add a lot of quality information because most of the software included in the other families could have been used in the cloud. It is also the case for data analysis and visualization tools such as ED and BDS. Both have a high possibility of being used in the cloud. In particular, the bundle of technologies showing ED and SaaS together has to be interpreted with caution because we don’t know whether it’s the ED that’s been used in the cloud and/or all the other software that the company has decided to adopt.

Third, the index used to count the number of technologies adopted has a weakness. It considers that all technologies play an equal role in terms of increasing the propensity to innovate, which is probably not true. For instance, an ERP might not have the same impact on innovation as a 3D printer. Nevertheless, the choice was made to confirm that a higher number of technologies will increase the propensity to innovate, regardless of what these technologies are. The different complementarities between technologies were explored with the market basket analysis in Chapter 6. The same can be said for the index of measures adopted. Some measures could have had a more prominent effect on the number of technologies adopted. In future research, this weakness could be mitigated by testing the most popular bundles against the propensity to innovate. While there might not be an optimal number of technologies to adopt, some specific bundles could yield more innovation than others.

The limits mentioned above are a good start to discuss potential future research. While it may be costly to do another survey, it is imperative that a new version of SAT be administered for various reasons. First, it can enable to focus on advanced technologies that may be more relevant to service firms by expanding the BI family technologies, for example. Second, advanced technologies can be complemented by emerging technologies to which they are precursors. For example, BDS will lead to AI, while RFID will lead to IoT. It would be interesting to compare if firms that adopted technologies were able to adopt emerging technologies in the future. Even without a new survey, there would be other avenues to explore in the future. Because the data has been collected in 2015, it would be possible to do survival and growth analysis on these firms. While the results have shown an increase in the propensity to innovate for firms who adopted new technologies, it would be pertinent to see how many firms survived and how many of them were able to keep growing despite the COVID-19 pandemic. Furthermore, the pandemic was an opportunity for firms to accelerate their digital transformation, which can be enabled by many of the technologies listed in the survey. A possible research path would be to see if technology adoption were indeed accelerated despite some firms being affected financially by the different lockdowns in Canada. Moreover, the study included a brief analysis based on a firm's characteristics for some specific bundles of technologies. However, a future path of research would be to push this analysis further by doing the research for more bundles of technologies and focus on technologies from input to output. In other words, association rules should be built across all families of technologies.

Furthermore, one element that can be improved in a future research would be to find solutions to visualize temporal rules. Contrary to static association rules that have many developed tools for mapping the rules, it was more difficult to map temporal rules. Instead, the selected approach was to find specific rules to two relevant technologies related to the fourth industrial revolution. A future research path would be to develop an efficient way to view the network of technologies being adopted, according to their time of adoption.

8.3 Research contributions

This thesis has many contributions on different levels, whether it is theoretical, methodological and practical. On the theoretical side, this study further develops the literature on technology adoption by providing a view of the interconnection between the different families of technologies, from input to output of the supply chain. Most of the papers already available on the topic focus on one type or one family of technology at a time. It also constitutes a good summary of the different technologies available and their benefits on a firm's performance (although not quantified).

This study also demonstrated the endogenous effect that technology adoption can have on innovation propensity. In addition to the importance of advanced technologies, this thesis included OI strategies, in particular collaboration and strategic alliances, and other business practices that are known to have a positive effect on innovation performance, such as cross-functional teams and outsourcing. The adoption of advanced technologies and collaboration practices were confirmed to be beneficial for firms in terms of increasing their innovation propensity. Despite the collaboration in the literature, this study did not find a significant effect on the propensity to innovate in the case of firms that have adopted DIC and PF technologies. In particular, science-intensive firms had a negative impact on non-technical innovations compared to the service sector, which suggests that firms adopting AMTs might gain more benefits leading to an increased innovation propensity because of these new technologies. The science-intensive firms are comprised of NAICS codes 334 and 3364, which represent computer and electronic manufacturing, and aerospace and products manufacturing respectively. High-tech companies are normally more prominent into technological innovation (process and product).

In terms of methodological contributions, this study is the first to use a market basket analysis (MBA) in the innovation management and technology adoption fields. Market basket analysis is a tool that is usually applied in marketing for e-commerce websites such as Amazon. However, it remains at an exploratory level when applied to survey data related to technology adoption and innovation management. This thesis contributed to explaining in detail the methods for using static and temporal association rules adapted to the context of technology adoption. The discussion of the results attempted to provide a sequential process to calculate and interpret association rules. The same can be said for the temporal rules that were described in Chapter 7. While the results provided a general guidance as to setting the threshold of the support, confidence and lift, the sample size of the different families of technologies were different from one another. As a consequence, the thresholds needed to be adapted respectively, but they can be considered as a rule of thumb for future research on similar survey data.

The practical contributions of this thesis are numerous. While a market basket analysis can traditionally be useful for companies selling these technologies, the most important advantages would be for the firms wanting to adopt new technologies. Recommended guidelines could be provided to companies to optimize their choice of technologies based on their needs and the best practices of each industry. The analysis provided insight into the beginnings of I4.0, which can constitute an extra motivation for companies that do not know which technologies to adopt. Furthermore, due to their elevated costs and the multiple available alternatives, smaller companies may find it difficult to adopt the right technologies. Governments can participate in providing the right guidelines paired with funding opportunities for adopting groups of technologies that are complementary and that will enable firms to increase their propensity to innovate. Moreover, these results can be used to develop and target policies within the superclusters initiative that have been created by the government of Canada with the goal of helping firms with the adoption of emerging technologies. For instance, the Scale AI supercluster aimed at promoting AI implementation could provide funding to firms seeking to adopt a BDS, which is an important prerequisite for larger firms seeking to take full advantage of their data.

8.4 Final words…

This research has been an opportunity to link the concepts of OI and technology adoption, both important factors that can influence the propensity to innovate. While the main focus was on advanced technologies, the study contributed to review an exhaustive list of technologies that can be utilized across different industries of the supply chain, from input to output. While many of the outcomes were in line with the literature, this study was also a medium to discover new methodologies. While the algorithm used provided pertinent information, the study was still exploratory and these new methods need to be utilized in other scenarios in the technology adoption field to validate their reliability in such contexts.

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APPENDIX A LITERATURE REVIEW ON THE CONCEPTS OF PROXIMITY

The concepts of proximity and interpersonal networks

One way to enable OI practices is for firms collaborate and share knowledge through clusters. When firms are close geographically, interaction and cooperation become easier. While being close has its advantages, it can also have negative effects such as increased competition. However, the negative effects do not outweigh the positive that comes out of a cluster. To understand the dynamics knowledge transfer, this section will define the different aspects of proximity and explain how it affects a firm's innovation performance. The main motive to briefly review clusters and proximity theory is to understand if it can affect OI and technology adoption, which will be reviewed later in this chapter. The most used definition of a cluster is certainly the one established by M. E. Porter (1998). He states that a cluster is a geographic concentration of interconnected firms and institutions in a specific industry. It can be interpreted differently because the cluster's boundaries are not clearly stated. According to Baptista and Swann (1998), the creation of a cluster can depend on multiple factors including a strong local demand, the market share, lower search costs and customer's feedback. On the other hand, they also studied the negative effects of a cluster and one of them was the increased competition. In fact, the closer in distance firms are, the more chances of increased competition between them. For a cluster to emerge, it takes the existence of an anchor firm that will attract the others (Wolfe & Gertler, 2004). The stronger the cluster becomes, the more it becomes attractive to those outside (Baptista & Swann, 1999). These results also suggest that the stronger the anchor firm, the stronger the cluster that can be created around it.

In the high-tech industry, or any industry for that matter, the physical proximity of firms and high education institutions becomes really important to foster collaboration. However, Coughlan (2014) argues that with the development of ICT tools, it is now possible for firms to rely on virtual proximity. This indicates that the geographical location is not the only thing that matters anymore to have increased collaboration between the different players. Physical proximity will always be important and some recent studies show that clusters have a positive impact on innovation and firm performance. For instance, Russian ICT firms that are in a cluster perform better (Samsonowa et al., 2012). Even though some clusters succeed in ensuring that firms innovate, some others fail meaning that the physical proximity might not be enough to define the dynamics of a cluster. Hassan and Abu Talib (2015) investigate an ICT cluster created similarly to Silicon Valley but it failed because the government and the firms were not aligned on the same goals. Another example of failure is a cluster in Montréal that was created in 1999. According to Letaifa and Rabeau (2013), the geographical proximity is a good start to foster collaboration and innovation but there is a social distance that denies firms from working together. This results in a competition where companies do not wish to share their knowledge (Letaifa & Rabeau, 2013). Since the physical proximity is no longer enough to define a cluster, it is important to discuss the different aspects of proximity that leads to interpersonal networks. R. Boschma (2005) distinguishes 5 types of proximity: cognitive, organizational, social, institutional, and geographical. The literature on technological proximity will be developed, which will be mostly relevant to explain technology adoption. Although they are related to each other, the following paragraphs will briefly define each type of proximity.

Cognitive proximity

Cognitive proximity can be defined as how similarly different players view and evaluate the world based on values, cultures, technologies and education (Wuyts, Colombo, Dutta, & Nooteboom, 2005). Firms will tend to fall into a routine when they search for new knowledge and although this can enable better communication, it can also decrease the level of innovation (R. Boschma, 2005). If firms want to be more innovative, they need to keep a cognitive distance which can be achieved by being open to the outside world in order to search for varied sources of knowledge (Saviotti, 1996). According to (Nooteboom, 2000), too much cognitive proximity will mean that there will be less innovation while too little cognitive proximity will imply a lack of communication. The former is good for collaboration but there will be a lack of innovation. In fact, firms or actors that see the world similarly will communicate effectively but won't have different opinions on a certain matter preventing them from innovating. Cognitive proximity in a cluster also leads to better knowledge acquisition which increases the innovation performance (Molina-Morales et al., 2011). Therefore, it is important to find the right balance of cognitive proximity just like it is with the other aspects of proximity that will be described in the next paragraphs.

Organizational proximity

Organizational proximity refers to the capacity of exchanging diverse information between different organizations (R. Boschma, 2005). Knowledge can be shared within an organization or between organizations. Networks facilitate the transfer of knowledge and information by coordinating transactions between organizations in a world that is constantly changing which makes it an uncertain environment (Cooke & Morgan, 1998). In fact, inter-firm collaboration can be more difficult to achieve unless the risks of intellectual properly are lowered. Furthermore, private-public collaborations tend to be even more difficult to achieve than inter-firm collaboration because of different incentive measures and time constraints (Ponds, Van Oort, & Frenken, 2007). It can be argued that there is a higher chance of collaborating when those incentives are shared between organizations. With better knowledge transfer, firms tend to do more cooperation because of the connection they have (Letaifa & Rabeau, 2013). The effect on innovation performance should be increased the more proximate organizations are. Consequently, this proximity makes firms more open to the outside world where the social context becomes crucial. The social proximity is described next.

Social proximity

Social proximity is defined by R. Boschma (2005) as the trust and interpersonal relations between actors and they are based on friendship, kinship and experience. Social proximity is required for organizations to be able to learn and innovate because it can facilitate the exchange of tacit knowledge that is more difficult to trade through markets (Maskell & Malmberg, 1999). For each interaction between two parties, there is this social aspect that is often neglected. When a firm has a sense of belonging to a network (or a cluster), it facilitates the exchange of information and thus promotes collaboration. Networks are viewed as interpersonal relationships between two actors (i.e. individuals) and, according to Ter Wal (2014), they strongly interact with geographical mechanisms. This behaviour can be explained by two reasons: (1) knowledge diffusion is facilitated by interpersonal channels that are based on friendship, kinship and experience (A. Agrawal, Cockburn, & McHale, 2003; A. Agrawal, Kapur, & McHale, 2008); (2) knowledge flows and networks are localized because individuals are not mobile in space (Breschi & Lissoni, 2009).

Consequently, social proximity can be viewed as a sense of belonging to a group whether its people, organizations or any other type of actors in a network. This is a really essential aspect because collaboration and knowledge transfer become easier when there is trust involved (Letaifa & Rabeau, 2013). Building trust results in deeper tie formation within the network. The roles of network ties have been investigated in the literature (Cassi & Plunket, 2015; Ter Wal, 2014). Closer connections (i.e. higher social proximity) may increase innovative performance through better access to knowledge. While social distance can promote diversity and new ideas, it can result in higher costs pertaining to managing different sources of knowledge (Sorenson, Rivkin, & Fleming, 2006).

Institutional proximity

Whereas social proximity was more of a micro-level analysis, the institutional proximity is more at the macro-level and the two are interrelated (R. Boschma, 2005). The latter refers to the cultural norms that control business and non-business relationships in a social context (Letaifa & Rabeau, 2013). Too much institutional proximity is not favourable to innovation while too little institutional proximity is detrimental to collective action and innovation (R. Boschma, 2005). This is why it is important to find the right balance of formal institutions linked with social proximity in order to foster innovation. In fact, when organizations are not located in the same institutional context, organizational and social proximity may not be enough to stimulate effective learning (Gertler, 2003). Since these three types of proximities seem to be linked, it is reasonable to believe that geographical proximity is also related to at least one of them.

Geographical proximity

According to J. R. Howells (2002), geographical proximity indicates the physical distance between individuals or firms. It provides an advantage to actors close to each other by allowing them direct access to information and knowledge through face-to-face contacts. In general, too little or too much proximity may decrease the propensity to innovate (R. Boschma, 2005; Broekel & Boschma, 2012). A short distance will favour communication between the players and enhance the exchange of information and tacit knowledge (R. Boschma, 2005). Furthermore, high proximity helps in reducing transportation costs, which makes it easier to have face-to-face interactions resulting in increased access to knowledge (Fleming, King III, & Juda, 2007). The geographic proximity plays a positive role when it comes to innovation (Letaifa & Rabeau, 2013) but recent studies on ecosystems of innovation highlight the role of interdependence (Iyer & Davenport, 2008; Siegel & Renko, 2012). This is because long distances may achieve closeness if there is complementary proximity involved (R. Boschma, 2005). However, innovation performance may be increased by this proximity as collocated firms have a higher probability to meet and collaborate (Beaudry & Breschi, 2003; Boufaden & Plunket, 2007). Furthermore, networks are demarcated by territory; therefore it would be wrong to assume knowledge spillovers are bounded by geographical proximity (Bunnell & Coe, 2001). In fact, geographical proximity may be hiding other channels in which information diffusion occurs (Broekel & Boschma, 2012; Huber, 2012).

Technological proximity

As was previously mentioned, several studies pointed to the fact that geographical proximity is not enough to enable innovation (R. Boschma, 2005; Cassi & Plunket, 2015; Mattes, 2012). According to (Bouba-Olga, Carrincazeaux, Coris, & Ferru, 2015), this type of proximity has been "overemphasized to the detriment of other proximity forms". In addition to the previous dimensions of proximity, the technological aspect that has been the most linked to innovation (Huber, 2012) will be described in this section. By definition, this concept is based on the notions of cognitive proximity (R. Boschma, 2005; Nooteboom, 1999, 2005). Lane and Lubatkin (1998) defined technological proximity as the overlapping knowledge between two partners. The other types of proximities are mostly viewed as coordination mechanisms. They represent knowledge flows and help facilitate the creation of new knowledge, but what matters most to improve innovation performance is the characteristics and the complementarity of knowledge bases between individuals (Nooteboom et al., 2007). While other dimensions of proximity focussed on the firm and its global knowledge, the dimension discussed here focus on the capacity to transfer tacit knowledge, which by nature is necessary to innovate (R. Boschma, 2005). Korbi and Chouki (2017) argued that to effectively transfer tacit knowledge, a firm requires a technological proximity with its partners. Many scholars have demonstrated the impact of technological proximity on innovation performance (Fafchamps, Van der Leij, & Goyal, 2010; Mowery, Oxley, & Silverman, 1998;

Nooteboom et al., 2007). For example, Nooteboom et al. (2007) linked this type of proximity to curvilinear relationship with innovation. They argue while actors need proximity to interact efficiently, technological distance grants the possibility to combine and profit different types of knowledge.

Summary and conclusion

The different concepts of proximities were explored in this section by positing that they are all interrelated. In terms of clusters, the first point of creation usually lies in the physical proximity of the firms. As was previously mentioned, there is an anchor firm that will attract the others in the same geographical space. Scholars have discussed the benefits of clusters. For example, Letaifa and Rabeau (2013) mention the different proximities to explain the lack of collaboration in the ICT industry in Canada. Schröder (2014) made a study about a cluster created in Cologne on two observations period: 10 years before the creation and 10 years after. He found that the cluster increased cooperation between the firms. Furthermore, the different aspects of proximity are not enough to understand the essence of clusters. There are many types of clusters whether they focus on research centres or on suppliers. Chiesa and Chiaroni (2005) define two types of clusters: spontaneous and policy-driven. The former is the result of the spontaneous co-presence or key factors while the latter is created by government implication. Tan (2006) investigated a science park, a type of policy-driven cluster which is the largest ICT cluster in China. He found that this cluster was victim of premature aging because of key factors such as the lack of entrepreneurial leadership, mechanisms to transfer technology from universities and venture capital. Despite the importance of clusters, it is worth noting that power in a cluster resides in the hands of actors who are able to build networks, maintain them and develop them to attract other actors (Smith, 2003), generally an anchor firm. In other words, a cluster is highly dependent on its network.

However, geographical proximity is not enough to explain the dynamics of interactions and innovation. Firms must have the right balance of different proximity dimensions in order to foster innovation. Because ICT tools allow firms to be close virtually, companies need to rely on interpersonal networks to increase their innovation performance. For example, cognitive proximity is useful to exchange information while increasing innovation performance. Furthermore, firms require institutional and organizational proximity with the right number of formal institutions which will result in an exchange of information with the outside world. Finally, social proximity is what will give a sense of belonging and makes sure that all the actors of a cluster or ecosystem are aligned towards the same objective. Furthermore, the aspect of social proximity becomes an important piece when discussing networks. With the right balance of social proximity, the relationships in the network remain healthy thus favouring collaboration which will in return enhance innovation. These proximities all help understand the dynamics in a network and the way firms collaborate. The aspect of technological proximity was also covered, which can also impact innovation performance. While technological distance can allow for different combinations of knowledge bases, it has been demonstrated that a higher proximity results in better interaction between firms (Nooteboom et al., 2007).

R. A. Boschma, Frenken, and Martin (2010) coined the term “proximity paradox” to explain the fact that there is an optimal proximity that may lead to increased innovation performance. While some proximity can facilitate interaction between actors, too much proximity can hurt innovation. According to Mattes (2012) innovation can be enabled by renewal based on complementary knowledge between firms, but also on the integration of similar knowledge guaranteed by proximity. Literature on proximity has provided some key insights about this paradox. For example, Capaldo and Petruzzelli (2014) explained that while proximity is an important determinant of innovation by improving learning and knowledge integration, it can also prevent access to heterogenous knowledge sources. In other words, the different concepts of proximities can result in a confronting effect on innovative performance regarding the creation and integration of new learnings. For these reasons, the most innovative firms are those who keep a medium proximity level with their partners (Fitjar, Huber, & Rodríguez-Pose, 2016).

APPENDIX B DESCRIPTIVE STATISTICS – VARIABLES USED IN REGRESSIONS

This appendix provides the full tables presenting the descriptive statistics of the variables used in the IVPR analysis. There are separated into three tables that provide respectively the samples for BI technologies (Table 8.1), DIC and PF technologies (Table 8.2), and MHSCL technologies (Table 8.3).

Table 8.1: BI Technologies - Descriptive Statistics

BI	mean	sd	skewness	kurtosis
allinno	0.858	0.349	-2.052	5.210
techinno	0.751	0.433	-1.159	2.342
nontechinno	0.742	0.438	-1.104	2.220
prodinno	0.580	0.494	-0.324	1.105
procinno	0.653	0.476	-0.645	1.416
markinno	0.517	0.500	-0.069	1.005
orginno	0.642	0.480	-0.592	1.351
OsloNew	0.825	0.380	-1.709	3.920
Collab-uni&gvt	0.200	0.400	1.499	3.247
Collab-firms	0.348	0.477	0.636	1.405
Concurrent Eng.	0.178	0.383	1.680	3.823
Cross-funct. Teams	0.279	0.449	0.987	1.974
Outsourcing	0.319	0.466	0.776	1.603
CTI-Benchmarking	0.153	0.360	1.930	4.724
Sustain. Dev-ESP	0.106	0.308	2.557	7.540
PDM & LCM	0.170	0.376	1.756	4.085
ln_size	4.082	1.411	0.841	3.944
ln_age	2.431	0.976	-0.615	2.875
inress	0.145	0.352	2.015	5.060
inlab	0.087	0.282	2.932	9.595
inscal	0.101	0.301	2.648	8.011
inspec	0.078	0.268	3.147	10.904
insci	0.051	0.220	4.075	17.604
ln_Index_BI	1.062	0.356	0.441	2.002
ln_Index_Measures	0.989	0.383	0.274	3.229
CAPEX_BI	1.936	1.918	0.134	1.239
Empl Recruit	0.293	0.456	0.907	1.823

Table 8.2: DIC and PF Technologies - Descriptive Statistics

DIC	mean	sd	skewness	kurtosis
allinno	0.902	0.298	-2.696	8.267
techinno	0.829	0.377	-1.744	4.042
nontechinno	0.770	0.421	-1.282	2.644
prodinno	0.649	0.477	-0.626	1.392
procinno	0.730	0.444	-1.037	2.076
markinno	0.520	0.500	-0.079	1.006
orginno	0.685	0.465	-0.796	1.633
OsloNew	0.862	0.345	-2.098	5.401
Concurrent Eng.	0.244	0.429	1.194	2.427
Cross-funct. Teams	0.337	0.473	0.689	1.475
Collab-uni&gvt	0.221	0.415	1.345	2.809
Collab-firms	0.363	0.481	0.572	1.327
CTI-Benchmarking	0.165	0.371	1.805	4.258
Sustain. Dev-ESP	0.100	0.300	2.669	8.125
PDM & LCM	0.184	0.388	1.630	3.656
Outsourcing	0.358	0.479	0.594	1.353
ln_size	4.155	1.340	0.806	4.083
ln_age	2.461	0.952	-0.613	2.861
inress	0.169	0.374	1.771	4.135
inlab	0.118	0.323	2.364	6.589
inscal	0.108	0.311	2.520	7.350
inspec	0.124	0.330	2.283	6.210
insci	0.069	0.253	3.410	12.630
ln_Index_DIC	1.368	0.538	-0.057	2.486
ln_Index_PF	0.500	0.619	0.843	2.472
ln_Index_Measures	1.022	0.402	0.331	2.967
CAPEX_DIC_PF	1.192	1.736	0.865	1.907
Empl Recruit	0.358	0.480	0.591	1.349

Table 8.3: Descriptive statistics of the MHSCL sample

MHSCL	N=2389	mean	sd	skewness	kurtosis
allinno	1951	0.817	0.387	-1.637	3.679
techinno	1705	0.714	0.452	-0.945	1.894
nontechinno	1667	0.698	0.459	-0.861	1.742
prodinno	1326	0.555	0.497	-0.222	1.049
procinno	1459	0.611	0.488	-0.454	1.206
markinno	1149	0.481	0.500	0.076	1.006
orginno	1405	0.588	0.492	-0.358	1.128
OsloNew	1859	0.778	0.416	-1.339	2.793
Concurrent Eng.	430	0.180	0.384	1.666	3.775
Cross-funct. Teams	610	0.255	0.436	1.122	2.259
Collab-uni&gvt	414	0.173	0.379	1.726	3.980
Collab-firms	710	0.297	0.457	0.888	1.788
CTI-Benchmarking	310	0.130	0.336	2.204	5.856
Sustain. Dev-ESP	202	0.085	0.278	2.986	9.919
PDM & LCM	353	0.148	0.355	1.985	4.941

Table 8.2: Descriptive statistics of the MHSCL sample (con’td and end)

Outsourcing	704	0.295	0.456	0.901	1.811
ln_size	9617	4.026	1.344	0.785	3.874
ln_age	5985	2.505	0.959	-0.660	2.998
Inress	368	0.154	0.361	1.917	4.674
Inlab	239	0.100	0.300	2.666	8.107
Inscal	239	0.100	0.300	2.666	8.107
Inspec	212	0.089	0.284	2.892	9.366
insci	148	0.062	0.241	3.634	14.208
ln_Index_MHSCL	2896	1.212	0.435	0.307	2.041
ln_Index_Measures	2351	0.984	0.377	0.376	3.206
CAPEX_MHSCL	4646	1.945	2.001	0.168	1.193
Empl Recruit	580	0.243	0.429	1.200	2.440

APPENDIX C FULL TABLES OF ASSOCIATION RULES

This appendix provides the full tables presenting all the association rules generated (sorted by support) by family of technologies. The rules are separated into four tables that provide information on rules respectively for MHSCL (Table 8.4), BI (Table 8.5), DIC (Table 8.6) and PF (Table 8.7) technologies.

Table 8.4: List of all association rules related to MHSCL

ID	LHS		RHS	S	C	L	N
S1	{SCCVS}	=>	{WMS}	0.168	0.692	1.571	590
S2	{SCCVS}	=>	{DF}	0.146	0.602	1.660	513
S3	{CRM, WMS}	=>	{DF}	0.121	0.626	1.725	425
S4	{CRM, DF}	=>	{WMS}	0.121	0.603	1.367	425
S5	{DF, SCCVS}	=>	{WMS}	0.111	0.758	1.720	389
S6	{SCCVS, WMS}	=>	{DF}	0.111	0.659	1.817	389
S7	{DF, TMS}	=>	{WMS}	0.098	0.739	1.677	346
S8	{CRM, SCCVS}	=>	{DF}	0.095	0.771	2.126	334
S9	{CRM, TMS}	=>	{WMS}	0.095	0.706	1.601	336
S10	{DF, SCCVS}	=>	{CRM}	0.095	0.651	1.425	334
S11	{SCCVS, TMS}	=>	{WMS}	0.094	0.802	1.819	332
S12	{CRM, SCCVS}	=>	{WMS}	0.091	0.741	1.681	321
S13	{DF, TMS}	=>	{CRM}	0.086	0.650	1.422	304
S14	{CRM, TMS}	=>	{DF}	0.086	0.639	1.760	304
S15	{DF, QR}	=>	{WMS}	0.084	0.617	1.400	295
S16	{SCCVS, TMS}	=>	{DF}	0.080	0.684	1.884	283
S17	{DF, TMS}	=>	{SCCVS}	0.080	0.605	2.498	283
S18	{CRM, SCCVS, WMS}	=>	{DF}	0.075	0.819	2.258	263
S19	{CRM, DF, SCCVS}	=>	{WMS}	0.075	0.787	1.786	263
S20	{DF, SCCVS, WMS}	=>	{CRM}	0.075	0.676	1.480	263
S21	{CRM, DF, WMS}	=>	{SCCVS}	0.075	0.619	2.557	263
S22	{SCCVS, TMS}	=>	{CRM}	0.074	0.626	1.369	259
S23	{CRM, DF, TMS}	=>	{WMS}	0.069	0.799	1.813	243
S24	{CRM, TMS, WMS}	=>	{DF}	0.069	0.723	1.994	243
S25	{DF, TMS, WMS}	=>	{CRM}	0.069	0.702	1.537	243
S26	{DF, SCCVS, TMS}	=>	{WMS}	0.068	0.841	1.907	238
S27	{SCCVS, TMS, WMS}	=>	{DF}	0.068	0.717	1.976	238
S28	{DF, TMS, WMS}	=>	{SCCVS}	0.068	0.688	2.842	238
S29	{DF, SCCVS, WMS}	=>	{TMS}	0.068	0.612	2.093	238

Table 8.4: List of all association rules related to MHSCL (cont'd and end)

S30	{CRM, SCCVS, TMS}	=>	{WMS}	0.062	0.838	1.900	217
S31	{CRM, SCCVS, WMS}	=>	{TMS}	0.062	0.676	2.313	217
S32	{SCCVS, TMS, WMS}	=>	{CRM}	0.062	0.654	1.431	217
S33	{CRM, TMS, WMS}	=>	{SCCVS}	0.062	0.646	2.668	217
S34	{CRM, SCCVS, TMS}	=>	{DF}	0.061	0.834	2.299	216
S35	{DF, SCCVS, TMS}	=>	{CRM}	0.061	0.763	1.671	216
S36	{CRM, DF, TMS}	=>	{SCCVS}	0.061	0.711	2.936	216
S37	{CRM, DF, SCCVS}	=>	{TMS}	0.061	0.647	2.212	216
S38	{QR, SCCVS}	=>	{WMS}	0.057	0.629	1.427	202
S39	{QR, TMS}	=>	{WMS}	0.057	0.626	1.420	201
S40	{CRM, DF, SCCVS, TMS}	=>	{WMS}	0.053	0.866	1.964	187
S41	{CRM, SCCVS, TMS, WMS}	=>	{DF}	0.053	0.862	2.375	187
S42	{DF, SCCVS, TMS, WMS}	=>	{CRM}	0.053	0.786	1.720	187
S43	{CRM, DF, TMS, WMS}	=>	{SCCVS}	0.053	0.770	3.179	187
S44	{CRM, DF, SCCVS, WMS}	=>	{TMS}	0.053	0.711	2.432	187

Table 8.5: List of all association rules related to BI

ID	**LHS**		**RHS**	**S**	**C**	**L**	**N**
S1	{}	=>	{SaaS}	0.515	0.515	1.000	1271
S2	{}	=>	{ED}	0.510	0.510	1.000	1257
S3	{IaaS}	=>	{SaaS}	0.273	0.841	1.633	674
S4	{SaaS}	=>	{IaaS}	0.273	0.53	1.633	674
S5	{BDS}	=>	{ED}	0.146	0.593	1.164	360
S6	{BDS}	=>	{RTM}	0.144	0.586	1.334	356
S7	{IaaS, RTM}	=>	{SaaS}	0.135	0.886	1.719	333
S8	{RTM, SaaS}	=>	{IaaS}	0.135	0.640	1.972	333
S9	{ED, IaaS}	=>	{SaaS}	0.133	0.877	1.702	327
S10	{ED, SaaS}	=>	{IaaS}	0.133	0.618	1.904	327
S11	{ED, RTM}	=>	{SaaS}	0.122	0.566	1.098	301
S12	{RTM, SaaS}	=>	{ED}	0.122	0.579	1.136	301
S13	{ED, SaaS}	=>	{RTM}	0.122	0.569	1.294	301
S14	{BDS, RTM}	=>	{ED}	0.097	0.674	1.323	240
S15	{BDS, ED}	=>	{RTM}	0.097	0.667	1.516	240
S16	{IaaS, RTM}	=>	{ED}	0.092	0.601	1.180	226
S17	{ED, IaaS}	=>	{RTM}	0.092	0.606	1.378	226
S18	{BDS, RTM}	=>	{SaaS}	0.086	0.596	1.156	212
S19	{BDS, SaaS}	=>	{RTM}	0.086	0.704	1.601	212

Table 8.5: List of all association rules related to BI (con’td and end)

S20	{ED, IaaS, RTM}	=>	{SaaS}	0.086	0.938	1.821	212
S21	{IaaS, RTM, SaaS}	=>	{ED}	0.086	0.637	1.249	212
S22	{ED, IaaS, SaaS}	=>	{RTM}	0.086	0.648	1.474	212
S23	{ED, RTM, SaaS}	=>	{IaaS}	0.086	0.704	2.169	212
S24	{BDS, ED}	=>	{SaaS}	0.085	0.581	1.127	209
S25	{BDS, SaaS}	=>	{ED}	0.085	0.694	1.363	209
S26	{BDS, IaaS}	=>	{SaaS}	0.084	0.900	1.746	206
S27	{BDS, SaaS}	=>	{IaaS}	0.084	0.684	2.108	206
S28	{BDS, IaaS}	=>	{RTM}	0.070	0.751	1.708	172
S29	{BDS, IaaS}	=>	{ED}	0.066	0.716	1.406	164
S30	{BDS, IaaS, RTM}	=>	{SaaS}	0.066	0.942	1.828	162
S31	{BDS, IaaS, SaaS}	=>	{RTM}	0.066	0.786	1.788	162
S32	{BDS, RTM, SaaS}	=>	{IaaS}	0.066	0.764	2.354	162
S33	{BDS, ED, RTM}	=>	{SaaS}	0.065	0.671	1.302	161
S34	{BDS, RTM, SaaS}	=>	{ED}	0.065	0.759	1.490	161
S35	{BDS, ED, SaaS}	=>	{RTM}	0.065	0.770	1.752	161
S36	{ED, RTM, SaaS}	=>	{BDS}	0.065	0.535	2.174	161
S37	{BDS, ED, IaaS}	=>	{SaaS}	0.063	0.951	1.846	156
S38	{BDS, IaaS, SaaS}	=>	{ED}	0.063	0.757	1.486	156
S39	{BDS, ED, SaaS}	=>	{IaaS}	0.063	0.746	2.299	156
S40	{BDS, IaaS, RTM}	=>	{ED}	0.054	0.773	1.518	133
S41	{BDS, ED, IaaS}	=>	{RTM}	0.054	0.811	1.844	133
S42	{BDS, ED, RTM}	=>	{IaaS}	0.054	0.554	1.707	133
S43	{ED, IaaS, RTM}	=>	{BDS}	0.054	0.588	2.392	133
S44	{BDS, ED, IaaS, RTM}	=>	{SaaS}	0.053	0.977	1.897	130
S45	{BDS, IaaS, RTM, SaaS}	=>	{ED}	0.053	0.802	1.575	130
S46	{BDS, ED, IaaS, SaaS}	=>	{RTM}	0.053	0.833	1.895	130
S47	{BDS, ED, RTM, SaaS}	=>	{IaaS}	0.053	0.807	2.487	130
S48	{ED, IaaS, RTM, SaaS}	=>	{BDS}	0.053	0.613	2.492	130

Table 8.6: List of all association rules related to DIC

ID	**LHS**		**RHS**	**S**	**C**	**L**	**N**
S1	{MRPII}	=>	{ERP}	0.154	0.734	1.710	586
S2	{ERP, WCP}	=>	{EDI}	0.119	0.713	1.350	455
S3	{EDI, MRPII}	=>	{ERP}	0.099	0.749	1.743	378
S4	{CAX, MRPII}	=>	{ERP}	0.095	0.766	1.785	361
S5	{VM}	=>	{CAX}	0.091	0.884	1.793	349

Table 8.6: List of all association rules related to DIC (con'td)

S6	{EDI, SI}	=>	{ERP}	0.083	0.703	1.637	315
S7	{CIM, EDI}	=>	{CAX}	0.082	0.705	1.431	313
S8	{WCP, WSN}	=>	{EDI}	0.080	0.718	1.359	306
S9	{EDI, WSN}	=>	{WCP}	0.080	0.730	2.030	306
S10	{CAX, SI}	=>	{ERP}	0.076	0.729	1.698	291
S11	{ERP, WSN}	=>	{EDI}	0.075	0.732	1.386	287
S12	{CIM, ERP}	=>	{CAX}	0.075	0.720	1.460	285
S13	{ERP, WSN}	=>	{WCP}	0.074	0.722	2.007	283
S14	{SI, WCP}	=>	{EDI}	0.073	0.736	1.393	279
S15	{SI, WCP}	=>	{ERP}	0.072	0.726	1.690	275
S16	{MRPII, WCP}	=>	{EDI}	0.072	0.729	1.379	274
S17	{MRPII, WCP}	=>	{ERP}	0.070	0.713	1.660	268
S18	{CAX, WSN}	=>	{EDI}	0.067	0.718	1.359	257
S19	{MRPII, SI}	=>	{ERP}	0.067	0.789	1.837	254
S20	{ASI, WSN}	=>	{WCP}	0.064	0.728	2.023	243
S21	{CIM, WSN}	=>	{WCP}	0.064	0.766	2.128	245
S22	{CIM, MRPII}	=>	{ERP}	0.064	0.735	1.712	244
S23	{ASI, CIM}	=>	{WCP}	0.061	0.737	2.050	233
S24	{CIM, MRPII}	=>	{CAX}	0.061	0.705	1.430	234
S25	{CAX, EDI, MRPII}	=>	{ERP}	0.061	0.797	1.857	232
S26	{ERP, MES}	=>	{EDI}	0.060	0.702	1.328	228
S27	{EDI, MES}	=>	{ERP}	0.060	0.740	1.724	228
S28	{MES, MRPII}	=>	{ERP}	0.059	0.782	1.821	226
S29	{EDI, MES}	=>	{CAX}	0.057	0.705	1.430	217
S30	{ASI, MRPII}	=>	{ERP}	0.057	0.747	1.741	216
S31	{ASI, MRPII}	=>	{EDI}	0.056	0.737	1.395	213
S32	{ERP, WCP, WSN}	=>	{EDI}	0.056	0.760	1.438	215
S33	{EDI, WCP, WSN}	=>	{ERP}	0.056	0.703	1.636	215
S34	{EDI, ERP, WSN}	=>	{WCP}	0.056	0.749	2.083	215
S35	{MRPII, WSN}	=>	{ERP}	0.055	0.760	1.770	209
S36	{MRPII, WSN}	=>	{EDI}	0.055	0.760	1.438	209
S37	{CIM, SI}	=>	{CAX}	0.055	0.720	1.461	211
S38	{CIM, SI}	=>	{WCP}	0.054	0.706	1.964	207
S39	{ERP, SI, WCP}	=>	{EDI}	0.054	0.749	1.418	206
S40	{EDI, SI, WCP}	=>	{ERP}	0.054	0.738	1.720	206
S41	{ERP, VM}	=>	{CAX}	0.053	0.899	1.824	204
S42	{SI, WSN}	=>	{ERP}	0.053	0.739	1.721	204
S43	{SI, WSN}	=>	{EDI}	0.053	0.736	1.392	203
S44	{EDI, VM}	=>	{CAX}	0.052	0.883	1.793	197
S45	{SI, WSN}	=>	{WCP}	0.052	0.725	2.015	200
S46	{ASI, ERP, WCP}	=>	{EDI}	0.052	0.734	1.390	199

Table 8.6: List of all association rules related to DIC (con'td and end)

S47	{ASI, EDI, ERP}	=>	{WCP}	0.052	0.711	1.976	199
S48	{CAX, CIM, WCP}	=>	{EDI}	0.052	0.711	1.345	199
S49	{CIM, EDI, WCP}	=>	{CAX}	0.052	0.708	1.437	199
S50	{ERP, MRPII, WCP}	=>	{EDI}	0.052	0.735	1.391	197
S51	{EDI, MRPII, WCP}	=>	{ERP}	0.052	0.719	1.674	197
S52	{MES, SI}	=>	{ERP}	0.051	0.783	1.824	195
S53	{CAX, EDI, SI}	=>	{ERP}	0.051	0.739	1.720	195
S54	{CIM, EDI, ERP}	=>	{CAX}	0.051	0.721	1.463	194
S55	{MES, WCP}	=>	{EDI}	0.050	0.716	1.356	192
S56	{ASI, SI}	=>	{WCP}	0.050	0.711	1.977	192
S57	{ASI, SI}	=>	{EDI}	0.050	0.707	1.339	191

Table 8.7: List of all association rules related to PF

ID	**LHS**		**RHS**	**S**	**C**	**L**	**N**
S1	{CNC, ROBS}	=>	{ROB}	0.077	0.688	2.583	117
S2	{LSR, ROB}	=>	{CNC}	0.062	0.772	1.613	95
S3	{3DM}	=>	{3DP}	0.055	0.748	4.210	83
S4	{LSR, ROBS}	=>	{CNC}	0.055	0.692	1.444	83
S5	{AMST, ROBS}	=>	{ROB}	0.054	0.612	2.297	82
S6	{AMST, ROB}	=>	{ROBS}	0.054	0.631	2.577	82
S7	{LSR, ROBS}	=>	{ROB}	0.051	0.642	2.408	77
S8	{LSR, ROB}	=>	{ROBS}	0.051	0.626	2.558	77
S9	{MM}	=>	{CNC}	0.047	0.855	1.786	71
S10	{AMST, CNC}	=>	{ROB}	0.047	0.637	2.391	72
S11	{AMST, CNC}	=>	{ROBS}	0.046	0.619	2.531	70
S12	{3DP, ROB}	=>	{CNC}	0.044	0.736	1.537	67
S13	{3DO}	=>	{3DP}	0.041	0.778	4.379	63
S14	{3DP, LSR}	=>	{CNC}	0.041	0.708	1.478	63
S15	{LSR, ROB, ROBS}	=>	{CNC}	0.040	0.792	1.654	61
S16	{CNC, LSR, ROBS}	=>	{ROB}	0.040	0.735	2.758	61
S17	{CNC, LSR, ROB}	=>	{ROBS}	0.040	0.642	2.624	61
S18	{FMS, LSR}	=>	{CNC}	0.039	0.694	1.449	59
S19	{FMS, ROB}	=>	{CNC}	0.039	0.686	1.432	59
S20	{FMS, ROBS}	=>	{ROB}	0.038	0.695	2.609	57
S21	{FMS, ROB}	=>	{ROBS}	0.038	0.663	2.708	57
S22	{3DP, ROBS}	=>	{CNC}	0.038	0.707	1.477	58
S23	{3DP, ROBS}	=>	{ROB}	0.037	0.683	2.563	56
S24	{3DP, ROB}	=>	{ROBS}	0.037	0.615	2.514	56
S25	{3DO}	=>	{CNC}	0.036	0.667	1.392	54

Table 8.7: List of all association rules related to PF (con’td and end)

S26	{FMS, ROBS}	=>	{CNC}	0.035	0.646	1.350	53
S27	{3DO}	=>	{3DM}	0.034	0.642	8.791	52
S28	{3DP, AMST}	=>	{CNC}	0.034	0.605	1.262	52
S29	{MEMS}	=>	{CNC}	0.033	0.649	1.356	50
S30	{3DM, 3DO}	=>	{3DP}	0.032	0.923	5.197	48
S31	{3DO, 3DP}	=>	{3DM}	0.032	0.762	10.433	48
S32	{AMST, CNC, ROBS}	=>	{ROB}	0.031	0.671	2.520	47
S33	{AMST, CNC, ROB}	=>	{ROBS}	0.031	0.653	2.667	47
S34	{3DM, CNC}	=>	{3DP}	0.030	0.738	4.153	45
S35	{FMS, ROB, ROBS}	=>	{CNC}	0.028	0.754	1.575	43
S36	{CNC, FMS, ROBS}	=>	{ROB}	0.028	0.811	3.045	43
S37	{CNC, FMS, ROB}	=>	{ROBS}	0.028	0.729	2.978	43
S38	{3DP, ROB, ROBS}	=>	{CNC}	0.028	0.768	1.603	43
S39	{3DP, CNC, ROBS}	=>	{ROB}	0.028	0.741	2.782	43
S40	{3DP, CNC, ROB}	=>	{ROBS}	0.028	0.642	2.622	43
S41	{3DP, LSR, ROB}	=>	{CNC}	0.027	0.891	1.861	41
S42	{3DP, CNC, LSR}	=>	{ROB}	0.027	0.651	2.442	41
S43	{3DP, CNC, ROB}	=>	{LSR}	0.027	0.612	2.274	41
S44	{AMST, LSR, ROB}	=>	{CNC}	0.027	0.788	1.646	41
S45	{AMST, CNC, LSR}	=>	{ROB}	0.027	0.672	2.523	41
S46	{3DO, 3DP}	=>	{CNC}	0.026	0.635	1.326	40
S47	{3DO, CNC}	=>	{3DP}	0.026	0.741	4.170	40
S48	{3DO, ROB}	=>	{CNC}	0.026	0.886	1.851	39
S49	{3DO, CNC}	=>	{ROB}	0.026	0.722	2.711	39
S50	{3DM, LSR}	=>	{3DP}	0.026	0.780	4.391	39
S51	{3DP, FMS}	=>	{CNC}	0.026	0.606	1.265	40
S52	{FMS, LSR, ROBS}	=>	{CNC}	0.026	0.830	1.733	39
S53	{CNC, FMS, LSR}	=>	{ROBS}	0.026	0.661	2.701	39
S54	{CNC, FMS, ROBS}	=>	{LSR}	0.026	0.736	2.735	39
S55	{FMS, LSR, ROB}	=>	{CNC}	0.026	0.780	1.629	39
S56	{CNC, FMS, LSR}	=>	{ROB}	0.026	0.661	2.481	39
S57	{CNC, FMS, ROB}	=>	{LSR}	0.026	0.661	2.457	39
S58	{AMST, LSR, ROBS}	=>	{CNC}	0.026	0.75	1.566	39
S59	{AMST, CNC, LSR}	=>	{ROBS}	0.026	0.639	2.612	39

APPENDIX D PARTIAL TABLE OF TEMPORAL RULES

This appendix provides a list of temporal rules with a lift greater than 1 (sorted by lift) for all families of technologies combined. These rules can be found in Table 8.8 below.

Table 8.8: List of temporal association rules with a lift greater than 1

ID	LHS (Previous)	RHS (Predicted)	S	C	L
L1	CAX, CNC	3DM	0.013	0.163	3.176
L2	CNC, ERP	3DP	0.010	0.196	2.642
L3	CAX, MRPII	3DM	0.010	0.134	2.613
L4	CNC	3DM	0.018	0.126	2.459
L5	CAX, ERP	3DM	0.016	0.122	2.373
L6	CAX, CNC	3DP	0.014	0.172	2.311
L7	CAX, ERP, EDI	3DP	0.010	0.155	2.088
L8	CAX, MRPII	3DP	0.011	0.150	2.018
L9	CAX, EDI	3DM	0.013	0.102	1.992
L10	CAX, ERP	3DP	0.017	0.135	1.818
L11	ROB	3DP	0.012	0.132	1.784
L12	CNC	3DP	0.019	0.131	1.763
L13	CAX, QR	3DP	0.010	0.126	1.690
L14	CAX, EDI	3DP	0.015	0.124	1.672
L15	CAX, WMS	3DP	0.010	0.124	1.663
L16	LSR	3DP	0.010	0.112	1.510
L17	CAX	3DP	0.038	0.106	1.427
L18	ERP, QR, EDI	ED, SaaS	0.010	0.146	1.394
L19	CAX, QR	ROBS	0.011	0.132	1.352
L20	ERP, MRPII	3DP	0.013	0.100	1.352
L21	WMS, ERP, QR, EDI, WCP	SaaS	0.011	0.366	1.352
L22	TMS, WMS, EDI, WCP	SaaS	0.010	0.355	1.309
L23	ERP, QR, EDI, WCP	SaaS	0.014	0.353	1.304
L24	WMS, ERP, EDI	ED, SaaS	0.011	0.136	1.300
L25	WMS, QR, EDI, WCP	SaaS	0.015	0.350	1.293
L26	WMS, EDI, WSN	SaaS	0.010	0.347	1.279
L27	CAX, ERP, QR, EDI	SaaS	0.011	0.340	1.256
L28	WMS, EDI, WCP	SaaS	0.020	0.333	1.230
L29	CAX, WMS	ROBS	0.010	0.120	1.228
L30	CAX, ERP	ROBS	0.015	0.119	1.225
L31	WMS, ERP, EDI, WCP	SaaS	0.013	0.332	1.225
L32	TMS, EDI, WCP	SaaS	0.013	0.330	1.220

Table 8.8: List of temporal association rules with a lift greater than 1 (con’td)

L33	DF, WMS, EDI, WCP	SaaS	0.011	0.325	1.200
L34	WMS, QR, EDI, WCP	IaaS, SaaS	0.010	0.236	1.188
L35	WMS, ERP, QR, EDI	SaaS	0.016	0.316	1.168
L36	WMS, ERP, QR, WCP	SaaS	0.013	0.314	1.158
L37	WMS, ERP, QR	ED, SaaS	0.011	0.121	1.153
L38	WMS, EDI, WCP	IaaS, SaaS	0.014	0.228	1.145
L39	TMS, WMS, WCP	SaaS	0.013	0.310	1.144
L40	ERP, EDI, WCP	BDS	0.014	0.198	1.141
L41	ERP, QR, EDI	SaaS	0.022	0.309	1.140
L42	DF, WMS, ERP, QR, EDI	SaaS	0.010	0.308	1.137
L43	CAX, WMS, ERP, QR	SaaS	0.011	0.307	1.132
L44	CAX, CRM, EDI	SaaS	0.011	0.304	1.123
L45	WMS, WCP, WSN	SaaS	0.010	0.302	1.116
L46	DF, ERP, EDI, WCP	SaaS	0.010	0.302	1.114
L47	ERP, EDI, WCP	SaaS	0.021	0.302	1.114
L48	DF, ERP, QR, EDI	SaaS	0.013	0.300	1.109
L49	CAX, WMS, ERP, EDI	SaaS	0.010	0.300	1.107
L50	ERP, WCP	ED, SaaS	0.012	0.116	1.106
L51	QR, EDI, WCP	SaaS	0.019	0.298	1.100
L52	ERP, QR, WCP	SaaS	0.017	0.297	1.095
L53	SCCVS, EDI, WCP	SaaS	0.012	0.297	1.095
L54	CAX, ERP, QR	SaaS	0.015	0.294	1.087
L55	TMS, ERP, EDI	SaaS	0.013	0.294	1.085
L56	DF, WMS, QR, EDI	SaaS	0.013	0.293	1.083
L57	CAX, QR, EDI	SaaS	0.013	0.293	1.080
L58	CAX, WMS, WCP	SaaS	0.010	0.293	1.080
L59	WMS, SI, EDI	SaaS	0.012	0.292	1.078
L60	TMS, QR, WCP	SaaS	0.011	0.290	1.071
L61	WMS, EDI	ED, SaaS	0.014	0.112	1.069
L62	CAX, SCCVS, ERP	SaaS	0.010	0.287	1.059
L63	WMS, SCCVS, ERP, EDI	SaaS	0.011	0.287	1.059
L64	CAX, WMS, EDI	SaaS	0.013	0.286	1.056
L65	ERP, EDI, WSN	SaaS	0.011	0.286	1.054
L66	WMS, QR, EDI	SaaS	0.022	0.284	1.050
L67	WMS, ERP, QR, EDI	IaaS, SaaS	0.010	0.209	1.050
L68	QR, EDI, WCP	BDS	0.012	0.182	1.049
L69	CNC	ROBS	0.015	0.102	1.048
L70	CAX, WMS, QR	SaaS	0.013	0.284	1.047
L71	ERP, QR, EDI	BDS	0.013	0.182	1.046
L72	ERP, QR, WCP	BDS	0.010	0.181	1.043

Table 8.8: List of temporal association rules with a lift greater than 1 (con’td and end)

L73	WMS, EDI, WCP	BDS	0.011	0.181	1.040
L74	WMS, ERP, EDI	SaaS	0.022	0.281	1.038
L75	DF, WMS, QR, WCP	SaaS	0.011	0.281	1.038
L76	CAX, ERP, QR, EDI	RTM	0.010	0.320	1.037
L77	WMS, ERP, WCP	SaaS	0.015	0.281	1.037
L78	CAX, ERP, QR	ED	0.022	0.427	1.036
L79	ERP, QR, EDI, WCP	RTM	0.012	0.319	1.035
L80	DF, EDI, WCP	SaaS	0.014	0.280	1.035
L81	ERP, QR, EDI	IaaS, SaaS	0.015	0.205	1.032
L82	WMS, QR, WCP	SaaS	0.019	0.279	1.031
L83	EDI, WSN	BDS	0.012	0.178	1.028
L84	ERP, EDI	ED, SaaS	0.017	0.108	1.027
L85	CAX, ERP, QR, EDI	ED	0.014	0.423	1.025
L86	CAX, ERP, QR	IaaS, SaaS	0.011	0.204	1.025
L87	SCCVS, ERP, EDI	SaaS	0.014	0.277	1.024
L88	DF, WMS, ERP, EDI	SaaS	0.014	0.277	1.024
L89	CAX, ERP, QR, WCP	ED	0.011	0.421	1.021
L90	ERP, QR	ED, SaaS	0.015	0.107	1.019
L91	SCCVS, QR, EDI	SaaS	0.013	0.274	1.013
L92	TMS, WMS, EDI	SaaS	0.015	0.274	1.012
L93	CAX, CNC, MRPII	ED	0.012	0.417	1.011
L94	DF, SCCVS, ERP, EDI	SaaS	0.010	0.274	1.010
L95	ERP, EDI, WCP	IaaS, SaaS	0.014	0.200	1.008
L96	TMS, QR, EDI	SaaS	0.012	0.272	1.005
L97	CAX, CNC, ERP	SaaS	0.010	0.272	1.005
L98	CAX, ERP, EDI	SaaS	0.018	0.271	1.001
L99	CNC, ERP	SI	0.011	0.215	1.001
L100	WMS, SCCVS, QR, EDI	SaaS	0.010	0.271	1.001