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Enough fuel in the tank: The drivers of competitive advantage among AI start-ups

By

David Cormier

Under the supervision of

Denis A. Grégoire

HEC MONTREAL

Research Director

Management Sciences

(Strategy)

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Sommaire

Ce mémoire s'intéresse à identifier quelques-unes des principales caractéristiques / composantes qu'une « jeune pousse » en haute technologie pourrait vouloir mettre de l’avant afin de maximiser ses chances de succès dans un programme de mentorat visant à accélérer sa croissance. Pour ce faire, la recherche met en lumière les facteurs qui apparaissent importants aux yeux des mentors/investisseurs et certaines caractéristiques et ressources clés de ces entreprises. J’ai réalisé cette recherche à l’aide de données d’un programme de mentorat destiné à soutenir la croissance de jeunes pousses misant sur des technologies d’intelligence artificielle : le Creative Destruction Lab de HEC Montréal. L'échantillon de l'étude se compose de l’ensemble des 98 entreprises ayant commencé le programme lors des deux cohortes des 2018-2019 et 2019-2020. Un codeur aveugle et moi avons codé les caractéristiques de toutes ces entreprises, sur la base des documents fournis lors de leur application au programme. Je teste ensuite quatre hypothèses sur l’influence des ressources sur les progrès de ces entreprises dans le programme. Bien que des résultats intéressants en découlent, les résultats ne supportent qu’une seule sous-hypothèse. Je discute des implications de ces résultats pour les entrepreneurs, gestionnaires et mentors participant à de tels programmes.

Mots clés: Intelligence artificielle, Start-up, RBV, programme entrepreneurial, critère d’investissements, capital de risque

Méthodes de recherche: Recherche qualitative, codage d’information qualitatives

Abstract

This memoire is interested in identifying some of the key characteristics/components that a high-tech start-up might want to emphasize in order to maximize its chances of success in a mentoring program aimed at accelerating its growth. To do so, the research highlights factors that appear important to mentors/investors and some key characteristics and resources of these companies. I conducted this research using data from a mentoring program designed to support the growth of start-ups based on artificial intelligence technologies: the Creative Destruction Lab at HEC Montreal. The study sample consists of all 98 companies that started the program in both the 2018-2019 and 2019-2020 cohorts. Based on the documents provided upon their application to the program, a blind coder and I coded the characteristics of all these ventures. I then test four hypotheses about the influence of resources on these firms' progress in the program. Although interesting results emerge, the results support only one sub-hypothesis. I discuss the implications of these results for entrepreneurs, managers, and mentors participating in such programs.

Keywords: Artificial intelligence, AI, Start-up, Resource-Based View, RBV, Entrepreneurial program, Investor criteria, Venture capitalist

Research Method: Qualitative research, coding of qualitative data

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Table of Contents

List of Figures

List of Tables

1 Introduction

Over the years, technology shaped and transformed our reality countless times. From the growth and worldwide adoption of the internet to the significant leap in digitalization of business activities and human relationships, innovation has always been at the core of this progress. Technology evolved drastically in the last decades due to the significant improvement of raw computing power and the ability to collect and mobilize data. This evolution impacted the size of their addressable markets, and the way organizations operate. These changes created opportunity but also challenges. As a student in strategy of management and an aspiring entrepreneur, the world of technological firms (from start-ups to public companies) always interested me as per what could be the next new idea and how one could effectively leverage it and ensure a superior performance.

Recently, a new type of technology has become a buzzword among researchers, entrepreneurs, investors and government officials: artificial intelligence. Artificial intelligence **(AI)** is in constant evolution but "*refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. The term may also be applied to any machine that exhibits traits associated with a human mind such as learning and problem-solving*"[i]. Its scope of applicability is quite large, and its implications are still to be fully grasped. Indeed, with its current estimated market reaching $58.3 billion and projected to $310 billion by 2026[ii] combined with the all-time low cost of debt, the interest for this sector is quite strong. Seeing the exponential growth and potential, many start-ups as well as technology giants hope to capture this opportunity. In the AI ecosystem, Montreal is one of the centers of excellence for research and entrepreneurship due to its academic achievements and renowned professors. In this context, my interest in studying AI start-ups' strategic characteristics and resources took shape.

While studying for my master's degree in management specializing in strategy, I was encouraged to volunteer as an information technology assistant with HEC Montreal's Creative Destruction Lab **(CDL-Montreal)**, a mentoring program for high-tech new ventures hosted by HEC Montreal. During my volunteering, I discovered that my long-term ambition would be to become an entrepreneur myself and that the domain of artificial intelligence was fascinating. From a research standpoint, I note that just like in real-life funding decisions, mentors-investors in the program could decide to mentor forward some ventures of withdraw their support to other start-ups (who would then be dropped from the program). Building on my emergent understanding of the research literatures on the resource-based view's emphasis on the internal strategic factors that support a firm's competitive advantage, I set out to better understand the considerations that explained these decisions. With the market parameters existing for all competitors, the choice an enterprise undertakes to grow, and pivot is derived from their available resources and how efficiently and effectively they used these resources. The importance of these decisions and mobilization of their resources is even more crucial in new venture's early stages when resources are scarce. To explore the drivers of the competitive advantage among AI start-ups, I thus investigate the following research question: What internal factors could increase the probability of succeeding in an entrepreneurial program?

2 Literature Review

In order to adequately address this research question, I conducted a literature review on the resource-based view of strategic management and investor selection criteria. I address the development of strategic management on the resource-based view then describe key publications regarding investor's criteria selection for investments. Following this review, I propose a conceptual framework consisting of 20 criteria based on entrepreneurship, strategy, and management concepts. These are separated by topics such as technological resources, financial resources, human resources, and location.

2.1 The resource-based view of strategy

In strategic management, the essence of a business' superior performance enabling it to sustain a competitive advantage on a market is a notion studied by many researchers. Indeed, in hopes of better understanding the factors impacting this advantage, multiple frameworks exist such as the external perspective (Porter 1980) and the internal perspective (Barney 1991). Even if these academic notions provide great insight, they suggest divergent sources of a firm's success. Throughout my masters' strategy classes, I explored many conceptual models portraying the success of an enterprise; still, the internal approach resonated the most with my action-oriented mentality with its emphasis on factors within the imminent control of a venture as being the source of a sustained competitive advantage. The empowering aspect of being able to create an advantage by focusing on the right resources and leveraging them efficiently amazes me. With this basis, resources and sustained competitive advantage are two concepts that need clear definitions. A firm's resources include all assets, capabilities, organizational processes, attributes, information, knowledge, and anything controlled by the firm, allowing them to exist on a market (Daft 1983). A sustained competitive advantage is when efforts from current and potential competitors to duplicate or replace a competitive advantage have ceased (Rumelt 1984).

I structured this first portion of the literature review on the internal perspective of a strategy around Jay Barney's (1991) Resource Based View theory **(RBV)** who proposes that a firm's sustained competitive advantage is due to the resources it holds when they are valuable, rare, inimitable, and non-substitutable **(VRIN)**. In such, I separated the review in three phases: VRIN, pre-VRIN, and post-VRIN. To provide a summary of all concepts mentioned in these three sections, Table 1 below presents all authors in chronological order with their main contributions.

Table 1.Conceptual review of Resource-based view of Strategy

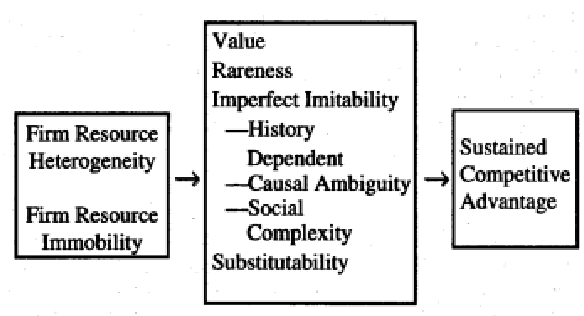
Authors	Source of competitive advantage
Edith Penrose (1959)	A firm's specific resources and the versatility of the resources allows organizations to succeed in a competitive market.
Karl Polany (1967)	The most valuable resources are sourced from tacit and implicit knowledge which is passed on willingly or indirectly within the organization by its employees.
Richard Daft (1983)	The growth of an organizations is highly liked to their information which they hold and their ability to process it.
Richard Rumelt (1984)	The business specifics have a greater impact on economic rent than the industry it exists in.
Birger Wernefelt (1984)	Resources in the firm which are heterogeneous, and immovable are the key to a successful business.
Donald C. Hambrick (1984)	Upper echelon theory suggests that the management's past experiences tint their judgement and their analysis of entrepreneurial problems and opportunities. Thus, the subjectivity of the managers adjusts the approach to the enterprise's objectives.
Ingemar Dierickx & Karel Cool (1989)	Asset accumulation is the core of the inimitability characteristic wanted by organizations in competitive markets. Unlike assets externally acquired, the accumulation process itself encompasses many effects that are hardly replicable like: time compression, interconnected resources, and causal ambiguity.
Richard Reed & Robert Defillippi (1990)	Causal ambiguity is the result of tacit behaviors, complexity and the specificity of a firm which creates entry barriers to imitation. Therefore, to preserve these barriers, continuous reinvestment in these competences is key.
C.K Prahalad & Gary Hamel (1990)	Core competences are the essence of sustained competitive advantages in the market are based of common factors of successful end products.
Jay Barney (1991)	Resource based view theory (RBV) places the reason of a sustained competitive advantage within the resources held in the organization. In order to be the source of an advantage, resources must be Valuable, Rare, Inimitable, and Non-substitutable.

C. Marlène Fiol (1991)	The unicity of an organization's culture acts as the catalyst of its differentiation on the market and is often the source of its competitive advantage.
Amit and Shoemaker (1993)	A firm's competitive advantage stems from imperfect and discretionary decisions made by managers facing uncertainty under their subjective impression of the market and existing resources
Alfred Chandler (1996)	The management's past experience highly influences the outgoing of management in the present.
David J.Teece (1997)	The ability of an organization to react and adapt by leveraging transversal competences with dynamic capabilities to a given problematic is often the source of their competitive advantage.
Christine Oliver (1997)	The ability of an organization to react and adapt by leveraging transversal competences to fit with its institutional context in a proactive and efficient manner is often the source of their competitive advantage
Danny Miller (2002)	The ability of an organization to assess and recognize the markets asymmetries vis-à-vis their own resources can be great to identify areas to improve and invest to gain or sustain market shares.
P. Jarzabowski (2006)	In strategic management the angle of analysis is driven by the knowledge intensity and environmental velocity intensity of the sector, to which a specific academic school is better suited to oriented decision makers of an organization and academic research.
Robert Grant (1993, 2008)	A firm's competitive advantage can only be sustained if its strategy leverages the ability of the managers to recognize the valued resources and mobilized them throughout the organization in sink. It is the whole interlinkage of the resources and decisions within the firm which really differentiates an organization from another.

2.1.1 VRIN (1991)

The Resource-Based View of the firm (Barney 1991) is often referenced as the center piece of the internal analysis in strategic management. The RBV framework (Figure 1) suggests that if the firm's resources are Valuable, Rare, Imperfectly Imitable, and Non-substitutable, they can allow a firm to gain a competitive advantage and sustain it over time.

Figure 1.RBV Framework (Barney 1991)



Based on the previous framework, resources can provide a sustained competitive advantage if they respect these four attributes:

- **Valuable:** Resources are considered valuable if they allow the firm to conceive or implement strategies that improve its efficiency by reducing internal costs and its effectiveness by increasing the perceived value to the end customer.
- **Rare:** Resources are considered rare when few competitors have them and/or are able to easily obtain them.
- **Inimitability:** Resources are considered inimitable when the competitors are unable to obtain or replicate them due to:
  - *Unique historical condition:* Where the performance of a firm at a given time and space does not solely depend on the external factors, industry, but mostly on its past and historical path to attain this moment. This unique history empowers the firm to utilize adequality the opportunities to maximize the implementation of value-creating strategies.
  - *Causal ambiguity*: Where the competitors do not understand the causal links between the resources and the performance, but if at least one individual within the advantaged organization does understand a fraction of this causal ambiguity, the competitive advantage becomes sustainable.
  - *Social complexity:* Where the social factors of employees are involved in the superior performance of the firm. This can refer to internal or external relationships, unique ways of using well-known resources, and the culture within a firm.

- **Non-Substitutability**: Where no other firm can reproduce the outcome, either by the combination of the same or different resources.

The VRIN framework gives a completely different point on view on the competitive advantage of a firm, by tracing it back from within versus being a result of external factors (market) as proposed by Michael Porter in 1980 with the Five Forces. With this internal approach, managers seeking a favorable position in a competitive market are encouraged to articulate their decisions in light of their resource allocation. All the resources and operations should then be graded on their value, rarity, inimitability, and non-substitutability. This framework can be used for intangible and tangible resources and increases the likelihood of investing in projects where key resources are mobilized and reinforced to solidify or grow market shares. By using this method, the organization benefits in the short term with a good return on investment and in the mid to long term perspective with the growth of competences and knowhow which increases the entry barriers to the market and the imitation possibility from competitors

2.1.2 Pre-VRIN (1959-1991)

The foundation of the RBV and the VRIN resides in the heterogeneity of firms in the same market with immoveable resources allowing a competitive advantage and growth to emerge (Penrose 1959 and Wernerfelt 1984). These characteristics offer many similarities with the Ricardian Economics (Ricardo 1833), where the most fertile lands, best immoveable resource, in a traditional profit maximizing-oriented market, can sustain lower prices in a competitive market and generate greater profits at equilibrium. At the core of this differentiation from competitors lies the inimitability of a resources as the source of the value of specific resources. In such, Dierickx and Cool (1989) suggested that asset accumulation is the primary driver of the inimitability of a resource making it valuable. Among many causes, the asset accumulation is driven by:

- *Time compression diseconomies:* where time is the driving factor of the value and inimitability an asset holds. The value of some resources can only arise after a long time has passed.
- *Asset mass efficiencies:* where the additional stock accumulation to an already existing high balance is easier due to the smaller marginal increment the increase represents versus the same growth in amount on a smaller existing balance. Hence, the sustainability of an advantage based on valuable assets accumulation favors entities with a large balance of a valued asset because they mobilize less effort to grow.
- *Asset interconnectedness*: since business units rarely operate in silos, they are often as good as their weakest link. Therefore, the ability to accumulate a specific valued asset may not solely be related to low levels of the aimed asset but perhaps the low levels of a resource facilitating the accumulation itself. This complementing asset, acting as a bottleneck instead of a facilitator to asset accumulation, thus limiting the value of the asset.
- *Asset erosion*: this relates to the rate an asset decays without maintenance. This principle suggests that there is value in accumulating assets but only if you can maintain its value. Assets with a high eroding rate usually require continuous maintenance or additional investments. Therefore, when allocating resources, one must analyze the initial return rate and the maintenance cost to sustain this return over time to truly assess its value.
- *Causal ambiguity:* where unidentifiable and uncontrollable variables are the underlining reason of the asset accumulation. This "secret sauce" may partially be understood by

managers but must remain unknown to competitors to create an advantage. Competencies that reside in the firm by tacit knowledge (Polany, 1967), complexity, and specificity (Reed & Defillippi, 1990) create this ambiguity since their reach, and initial creation are rarely explicit.

With this importance associated to assets, Prahalad & Hamel (1990) proposed that the roots of successful products are the core of a sustained competitive advantage's essence. They demonstrated that amongst these end products, we could carve out core products and then core competencies on which entities should focus to increase their likelihood of traction on markets. The typical example of this approach is the Honda entry in the North American market case from the late 1970's with their successful diagnosis after many years that the essence to their success was their engine's engineering competences. Indeed, after many studies, they understood that the engine was the common factor in their most popular products: motorcycle, car, or lawnmower. Thus, they decided to focus their branding and resources around this component. Therefore, their engine engineering became their business essence, leading them to create the Honda we know today. Resembling the VRIN attributes, Prahalad and Hamel suggest that to identify these core competencies, these must answer the following conditions:

- They must make a significant contribution to the perceived customer in the end product.
- They must be difficult to imitate.
- They must provide potential to access a wide variety of markets.

Once identified, the choice of specific projects should solicit these key core competences.

2.1.3 Post-VRIN (1991-Today)

Following the theoretical proposition by Jay Barney, Robert Grant (1991) suggested an augmented perspective of the resource-based view with its integration with the firm's strategy. His theoretical additions suggest that it is not only the resources or the capabilities that enable the creation of a proper strategy to gain an advantage over competitors but rather the understanding of the relationships between all moving parts within the firm. This concept of internal assessment is in sync with the recognized value chain theory (Porter 1985), which underlines all the moving parts allowing value creation. Notwithstanding being from different schools of thought, internal and external, adaptability is a common characteristic of successful firms for multiple authors. Along these lines, the firm's ability to recognize its asymmetries on a given market (Miller 2002), its ability to modify its resources to better seize opportunities with dynamic capabilities (Teece 1997), and to their unique institutional context (Oliver 1997) highly influences the sustainability of the advantage.

Succeeding the previous abstract concepts interlinking resources, the resource-based view of a competitive advantage portrays the complexity and exhaustivity of characteristics of a firm. In an attempt to deconstruct a firm to lay out its resources accurately, one can distinguish three types of resources: Tangible, Intangible, and Human (Grant 2008). This framework forms an important foundation of analysis for the research at hand. Tangible resources are usually more easily identifiable and quantifiable. Indeed, we can include financial resources such as cash, securities, borrowing capacity, and physical assets, including land, equipment, and real estate, all of which appear on financial statements. Nevertheless, the accounting value provided by this evaluation may portray vital information but does not encompass the strategic value of a resource, which attempts to measure its value at t+1. Oppositely, some intangible resources, i.e., Goodwill, include this strategic value perspective. Within these we can include technology, reputation, and culture (Fiol 1991). In the same matter, human resources are hardly quantifiable on a balance sheet since they primarily consist of expertise and abilities provided by employees. Inside this category, we can include organizational capabilities that allow all resources to create value by being adequately mobilized to be productive. The skills and know-how are essential to the previous and echo the core competence concept (Prahalad & Hamel 1990) previously addressed. This category equally accounts for the individuals who exhibit these competences. Indeed, executives should not overlook the importance of the experience of key employees and their management style as it can often be the source of competences and resources productivity (Hambrick 1984, Amit & Shoemaker 1993, Chandler 1996)

Having covered the essence and development of the resource-based theory, the previous models and strategic proposals should provide sufficient information to adequately inform stakeholders and key executives with resource allocation decisions to meet their objectives by mobilizing what they directly control. With the firm's success in mind, thus generating the greatest possible returns, the firms exhibiting some of the aforementioned characteristics should be more likely to be success stories, hence attracting financial support, bridging us to the following topic: investors criteria.

2.2 Investor selection criteria

Financial support is a steppingstone for many technological start-ups. Once all personal funds and family and friends’ donations are used, growing a high-potential technology-centered new business requires external support from equity investors like angels and venture capitalists. This type of funding can be a steppingstone for many start-ups before significantly scaling. Indeed, ventures that are backed by venture capitalists see their success rate drastically improve (Knight & Dorsey 1976). Seeing the importance of this step, understanding the selection preference of investors is essential for any venture wanting to increase their likelihood of obtaining support from investors. The following goes over the evolution of the academic literature to better understand what could impact Business Angel **(BA)** or Venture Capital **(VC)** interest to invest or support a venture in its early stages, thus promoting a venture to progress in CDL.

Unlike the previous literature review, which remained aligned throughout authors and concepts, the following is an amalgamation of multiple views and results on the same subject, separated by their step in the deal analysis flow. Investors usually fall under BAs or VCs and their criteria for investing slightly vary; hence it is always specified to provide a greater understanding of their decision process.

2.2.1 Deal screening

Among the first academic writers to publish on the topic, Tyebjee & Bruno (1984) investigated the process and criteria used by VCs in assessing investment opportunities. They decomposed the investment process into five steps: Deal origination, Deal Screening, Deal Evaluation, Deal Structuring, and Post-investment. Of importance for my study, they report that in Step 2, Deal screening, the management skills and history were essential, followed by the market size, the rate of return, and a fit between the investor's expertise and the start-up's niche market. Based on the latter criteria, the existence of a fit between the investor's industry and the start-ups and their location were determining factors. Investors seemed to prefer deals that would reflect the investment style of their portfolio, suggesting a possible agency theory issue (Jensen 1976) and promoting deals in a familiar market with new technologies and preferred products in a Business-to-Business Model. The previous findings resonate well with Poindexter's (1976) key factor of management quality and Wells' (1974) management commitment.

Still with respect to investors' initial assessment of a venture prospect, MacMillan, Siegel, & Narasihma (1985) showed that investors' most sought-after criterion concerns the management team but, more specifically, the entrepreneur's experience and personality, mentioning that even if the product, market, and financial structure are great, the leader is accountable for success of the business.

Using a method that allowed them to focus on actual selection decisions, Hall & Hofer (1993) found that VCs' main screening criteria were the fit between the venture and the lending guidelines of the portfolio, and the profitability of the industry addressed by the venture. Indeed, the investors would overlook the venture itself (internal factors) vis-à-vis the industry (external factor). As an example, the attractiveness of a specific industry could outweigh the lack of specific intellectual property protecting the start-up. The internal characteristics are in arm's length of the investors versus the industry itself has a much larger scheme of complex factors impacting its state, therefore it is harder for investors to adjust it to their liking. These results align well with the agency theory previously mentioned which are more focused on the market than the business. This importance allocated by VCs to the market and their portfolio fit were also findings in Bachher's and Guild's (1996) research which focused on Canadian equity investment regarding business angels, private venture capital firms, and public venture capital funds.

2.2.2 Deal evaluation

When evaluating a possible deal for a start-up, Tyebjee & Bruno (1984) observed that four different aspects were vital in assessing the riskiness and potential of the proposal: Marketing factors and their management, the product's competitive advantage, the quality of the administration, and the exposure to risk beyond the control of the venture. Amid similarities between factors of screening and evaluation, the existence of differences suggests the difficulty with which investors can genuinely understand their rationale and thought process during these decisions. The previous is a common theme throughout the literature.

2.2.3 Deal proposal

Typical start-ups seeking financing are not solely left to deal with venture capitalists; private investors or angel investors are also alternatives. Usually, a business angel's transaction size tends to be smaller; however, with the increased number of BAs and VCs, it is not uncommon to see a team of BAs financing a typical VCs size deal. Therefore, an analysis of their investing patterns and process is crucial for new enterprises seeking any influx of money. On this subject, Landstorm (1998) studied the investment criteria of private investors in the range of BAs in Sweden. His study concluded that the key factors significantly impactful in the decision-making process of investors were mainly attributable to the entrepreneur themselves. Indeed, most BAs hoped for a form of extension of themselves in the entrepreneur as they saw the investment as a continuation of their entrepreneurial adventure and considered themselves co-entrepreneurs once invested. The top three investment factors were the entrepreneur and management team, the market potential, and the fit between the entrepreneur's experience, the proposal, and the investors. Again, this shows that investors mostly cared about the entrepreneur without disregarding the venture's business and market potential. These realizations are also in the same spirit as Sudek’s (2006) results, who observed and interviewed BAs in California. They ranked the trustworthiness and enthusiasm of the entrepreneur, the quality of the management team, and the exit opportunity as top criteria. Therefore, portraying the importance of the entrepreneur and the similarities in standards amid geographical differences.

Seeing the importance of fit between the entrepreneur, the investor, and the financing guidelines throughout literature, accurately knowing the type of investor can significantly help ventures seeking financing. In this mindset, Osnaburgge & Robinson (2001) assessed if any differences in investment criteria existed between VCs in the technology sector vs. regular VCs. It turns out technology VCs placed greater emphasis on scalable factors such as the growth potential of the market and the product's overall competitive protection. The regular VCs dedicated greater importance to entrepreneurial factors such as the entrepreneur's expertise and track record.

This importance of an entrepreneur's past experiences was also expressed by Chandler (1996) as a significant added value when similarities between the entrepreneur's previous business context and their current context existed. The human capital of ventures always seems to be amongst the top factors for investment decisions (Bachher & Guild 1996). One reason for the previous could be the limited reliability and accuracy of realized audit and due diligence on a venture's tangible resource and market anticipations. Thus, leaving the investors the only "real" information on the opportunity being the individuals running the show. Likewise, even when all the other factors in the venture are attractive, if the team backing the operations cannot do anything and exploit their skills and the opportunity, the desirable business components hold little to no value. More so, on this uncertainty, Beckman (2002) observed that ventures which were too innovative were less likely to obtain financing since the proposal would be too far out of the VC's knowledge, raising the information asymmetry between the investor and the entrepreneur, thus increasing the risk for their portfolio. However, the prominence of the entrepreneur reduced this perceived uncertainty and could redirect investment decisions, reiterating the importance of the entrepreneur in obtaining financing. In a later study, Beckman (2007) observed that a diverse and experienced management team regarding their previous employers and competencies increased their likelihood to obtain financing. Conflictingly, previous experience in start-ups which intuitively would be a great signal did not reveal to be correlated with successful financing.

2.2.4 R&D programs

In another research context, Thomas Astebro (2004) observed 561 research and development projects that were selected as potential commercial success and studied their likelihood of reaching market commercialization. In the previous, 36 characteristics were analyzed regarding their probability of correctly predicting market reach. Based on the data collected, four criteria carried the most significant predictive power: expected profitability, technological opportunity, development risk, and appropriability conditions. The previous is much closer to the technical resources rather than the entrepreneurial characteristic proposed by many researchers.

2.3 Conclusion

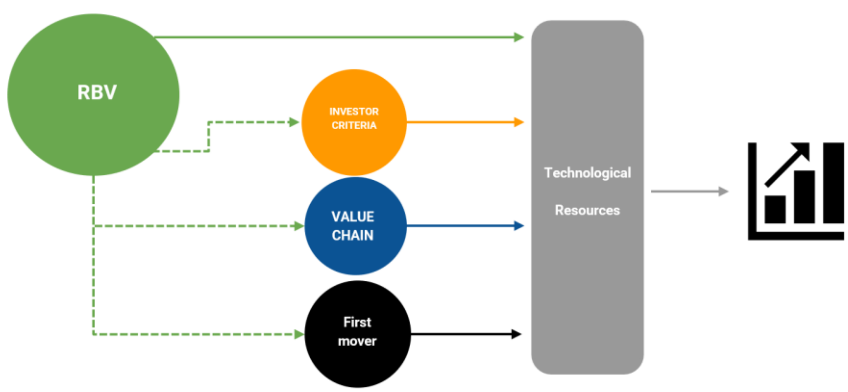
Considering the previous literature reviews on the resource-based view of strategy and the entrepreneurial criteria sought by investors, I propose that internal resources form critical drivers for the progression of a business and important selection criteria for investors.

Interestingly, however, I note that the business entities primarily studied in this two-research stream might differ in important non-trivial ways. On one hand, research drawing from the resource-based view typically concerns the challenges and realities of mid and large-sized organizations in established industries and markets (since the quantification of resources is more straightforward when a significant amount of it exists). On the other hand, research on investors' selection criteria typically concerns embryonic entrepreneurial ventures that attempt to develop and bring to market innovative new products, services, and other business models. Considering this difference, a question arises: Do the RBV principles increase a start-up's likelihood of progressing in an entrepreneurial program?

3 Conceptual framework

The research's objective is to understand what makes a start-up in artificial intelligence more likely to move forward in an entrepreneurial program. This specific industry, artificial intelligence, is a fast-paced environment that goes through rapid changes in priorities and interests and requires considerable competences and knowledge to succeed. With these components, Jarzabkowski (2006) would characterize this environment as a high competence/knowledge environment and would fall under the capacity building school, which is better analyzed by studying the internal characteristics of organizations. Additionally, empirical evidence suggests that the level of performance is primarily attributable to the structure of resources rather than the industry's structure (Galvin 2008). In complement, given the CDL context of the mentors being venture capitalists or angel investors and the voters for a start-up's progression, their point of view is critical. Hence, the previous literature reviews on the resource-based view and investor’s criteria fueled the conceptual framework proposed on Figure 2.

Figure 2.Conceptual framework



The RBV concepts and notions motivate the conceptual framework’s focus on the strategic influence of technological resources. This specific emphasis on technological resources is essential to start-ups and investors in this sector. New technological improvements often allow the holder of this technology to have an edge on its market, suggesting a competitive advantage. Assuming that a technology is new, valuable, unique, and hopefully protected, it should foster a venture's success (Barney 1991). By extension, a new venture’s technological resources could not only provide basis for growth, but it could favorably influence mentors’ and investors’ perception that a venture has what it takes to pursue that growth. Building on the reviews above, I focused my research on four technological strategic considerations that are typical in high-tech ventures, namely intellectual property, data access, prototype status, and applicability.

3.1 Technological resources

3.1.1 Intellectual property

In all businesses, intellectual property **(IP)** plays a key role in the uniqueness of the value proposition offered to the market vis-à-vis its competitors. Intellectual property encompasses ways of operating, trade secrets, and patents which are all owned and entitled to the business. This type of asset is well in line with the sub-criteria of the RBV framework of Barney (1991) by being rare and inimitable but is subject to substitutability and can hold no material value. As proposed by Mann & Sager (2007), the importance of a form of legal differentiation (patents) within an organization would act as a positive signal in the decision-making process and the amount of investment provided by venture capital firms. Additionally, Bachher & Guild (1996) illustrate that legally binding resources would create an entry barrier, like the theory of external forces of Michael Porter (1985), thus reassuring VCs as it would be considered an investment risk mitigation strategy.

On this basis, I propose to test the following sub-hypotheses, distinguishing between the efficacy of two different forms of IP strategies: formal and informal. Formal strategies concerns patents and property rights, and informal represent trade secrets. With Hypothesis 1a, I propose that intellectual property of any kind would be a strong indicator of the ability of a start-up to demonstrate or signal their value to progress in CDL. It would also suggest that a rare and unique resource holds value for these programs.

H1.A: Start-ups with well-defined IP strategies already in place (patents, trademarks, trade secrets, etc.) increase their probability of success in an entrepreneurial program.

With Hypothesis 1b, I propose that patents and property rights would be a solid indicator to investors that their start-up is valuable, rare, inimitable, and unique, thus promoting CDL progression. It would also suggest that investors prefer a formal form of intellectual property vis-à-vis the informal type, such as a secret sauce.

H1.B: Start-ups with IP strategies resting on patents and property rights are more likely to succeed in the program than start-ups with other forms of IP strategies.

3.1.2 Data access

In artificial intelligence, data plays a vital role in realizing machine learning operations by allowing them to run and provide value for the business. Indirectly, the capability of an organization to access a significant amount of data of good quality can enable an accurate and effective AI and thus reduce the venture's time to market to test its value proposition. As Mamonov & Triantoro (2017) pointed out, the time between data collection and data usage could impact the competitive advantage created by the data itself since its quality and pertinence might be compromised. However, access to data is often centralized and not always readily available, thus possibly hindering the model creation, testing, and operationalization. Consequently, since data is needed to run any models, start-ups who cannot collect data on their own rely on external partners to provide them with either transformed data or raw data. So, the collection method could be a critical factor to the data quality powering the value proposition of the start-up. Therefore, a more detailed distinction by type of data access regarding the collection method is proposed. The study identifies ventures that collected data by external means either from publicly available sources or from an alliance with other players and ventures who collect data autonomously. In such, I then propose two sub-hypotheses on data access.

3.1.2.1 ***Access to external data***

According to Dyer & Singh (1998), the collaboration between two entities with diverse activities and complementary resources to their operations can differentiate themselves in their respective markets with the establishment of a relationship (alliance) by an exchange of resources in order to yield a profit not achievable without this linkage. Investors often seek out opportunities in known markets to reduce their investment risk. Therefore, a start-up might operate in market A but leverage market B data in which the investor is very familiar, thus increasing their likelihood of investment or progression in CDL. If this collaboration generates success for both parties, this type of alliance can become an example for peers and promote this new way of mobilizing resources and eventually become a new market standard. Consequently, being the pioneers of leveraging unused data in a new way could be a considerable gain, as proposed in Marvin and Montgomery's first movers' advantage (1988). However, obtaining external data can also be done without any formal agreement by leveraging publicly available data, which could limit the uniqueness of the data obtained and shorten the advantage provided by this new resource given its general availability to competitors.

On this basis, I propose to test the following sub-hypothesis. With Hypothesis 2a, I propose that a privileged access to specific data from an external provider due to an agreement or if the data is outright owned by the venture would promote a progression in CDL. An underlying assumption is that the ability to build and maintain a relationship with a data supplier, who is most likely a major technology actor since most of the data on the market is held by a few, would suggest multiple other model application since the size and extent of their stored data could hold other utilities.

> **H2.A: Start-ups who have a privileged access to data to develop their Ai models are more likely to succeed in an entrepreneurial program.**

*3.1.2.2 **Internal data collection***

Collecting data (internally) through the company's methods, either via physical or digital means, incorporates the abovementioned advantages without the need for an agreement with an external entity. This significantly reduces the risks and the external forces on the start-up by limiting its supplier's power and allowing it to position itself in a free market environment with more room to maneuver Porter (1980). Indirectly, the resource-based view with the stock collection advantage proposed by Dierickx & Cool (1989) powers the entry barrier concept by Porter (1980). Equally, this aspect of difficulty penetrating a market by competitors can often be desirable to investors. Collecting in-house data provides an excellent leeway for the data analytics team to prescribe the ideal data requirements needed to train and develop their AI models adequately, thus enhancing the value chain (Porter 1985). However, the limitation of risks and supplier pressure is equally inexistent in the externally acquired publicly available data scenario, but internally collected data limits the exposure to data quality and quantity risks.

With the previous collection methods, data resonates well with the RBV concepts with its value, rarity, and non-substitutability. To the investors, it can act as a complementary resource to their other ventures, possibly acting as reassurance on an unknown market and provide an entry barrier. Also, the greater the control is obtained on the data, the more limited the supplier power is, and the greater the value chain bonifications are likely.

On this basis, I propose to test the following sub-hypothesis. With Hypothesis 2b, I propose that inhouse collected data would promote CDL progression. By collecting the data internally, this data would become proprietary and perfectly adapted the AI model requirement limiting the lag time between model testing, validating, and implementing.

> **H2.B: Start-ups who collect their own data to develop their Ai models are more likely to succeed in an entrepreneurial program.**

3.1.3 Applicability of the technology and its scope

With the plurality of artificial intelligence applications, investors could be seeking ventures that can leverage their algorithmic models in multiple industries. Indeed, since this is in a new market, the investor's knowledge is unlikely to be precisely aligned with the intended use of the start-up's technology. Therefore, a technology that can be adjusted in other sectors could be of greater interest. Transferability is an underlying concept of the RBV framework, with its initial proposal from Penrose (1959) gravitating around resources mainly being useful when they can be transferred within the firm to increase its productivity. This characteristic nourishes the Value criteria of the RBV (1991) and aligns itself very well with the value chain empowerment concept (1985). Indeed, the power of business models in the AI sector is the optimization purpose of most of the algorithmic models. Therefore, the inclusion of a new AI model in another sector of activity or even another enterprise is expected to increase the efficiency of the recipient. Equally, this transfer between two markets or two organizations is a trigger point for many investors on another known market as per the complementarity of resources to have both parties gain an economic advantage (Dyer & Singh 1998).

On this basis, I propose to test the following sub-hypotheses, distinguishing between the efficacy of having a business model that can be easily adjusted and one that can be directly transferred. With Hypothesis 3a., I propose that the aspect of transposability of an AI model to other industries is attractive and promotes progression in CDL. Equally, we suppose that even if a few adjustments are needed, the concept is still regarded as attractive and promising.

> **H3.A: Start-ups who operate with a business model mobilizing a type of Ai which can be leveraged in other industries are more likely to succeed in an entrepreneurial program.**

With Hypothesis 3b, I propose that the aspect of a direct transposability of anAI model to other industries is attractive and promotes progression in CDL. Equally, we suppose that solely the ventures which hold an AI model that would require no adjustments for transferability are attractive and promising.

H3.B: Start-ups who operate with a business model mobilizing a type of Ai which can be directly used in other industries are more likely to succeed in an entrepreneurial program.

3.1.4 Prototype

For a start-up, the progression towards a pilot stage, an MVP, or a prototype is the objective of many and a daily struggle. Once created, the precedent is likely to confirm a market fit or generate an entrepreneurial pivot to better serve the desired market. It is natural then that an investor would be interested in understanding where a venture stands in this progression. Equally, the deployment of their value proposition on the market greatly reduces the uncertainty around high-tech ventures with actual traction in “real life”. The materialization of a value proposition is an excellent indicator that the organization's value chain is somewhat effective. Equally, the technology industry being a race to the newest thing, a prototype could be a first movers’ advantage (1993) in the eye of many investors and competitors. This concretization of thoughts also encompasses core concepts of the RBV by being Valuable, if the market reciprocates with interest in the new product, Rare since getting to this stage is no easy task and finally Inimitable given it is likely patent protected and that if not, it can be more easily legally protected by other measures given its tangibility. Also, with a prototype or an available product, the venture can generate revenues which would be the greatest signal for investors Asterbro (2004) and even supersede the importance of the entrepreneur for Hall & Hofer (1993).

On this basis, I propose to test the following sub-hypotheses, distinguishing between the efficacy of having or not fully deployed a prototype. With Hypothesis 4a, I propose that the materialization of an idea in any way from a pilot to a prototype is a strong signal of potential progression in CDL. We suppose that this type of confirmation of ability to deliver on ambitions could signal to potential investors that the project has real traction and is more likely to use raised funds adequately.

H4.A: Start-ups who have already started deploying either a prototype or pilot tests in their market are more likely to succeed in an entrepreneurial program

With Hypothesis 4b, I propose that solely the materialization of an idea in any way which could generate revenues such as an MVP is a strong signal of potential progression in CDL. I suppose that this type of confirmation of ability to deliver on ambitions could signal to potential investors a quicker ROI.

H4.B: Start-ups who have already deployed a prototype (MVP) in their market which could generate revenues are more likely to succeed in an entrepreneurial program than start-ups who have only deployed pilot tests.

In order to differentiate these four hypotheses, I presented and positioned them on the graphic below driven by tangibility and traceability likelihood quadrants in Figure 4. Also, the legend Figure 4 illustrates the academic concepts behind the leading causes to test each hypothesis. The tangibility axis represents the level of materiality the hypothesis suggests, with its maximum being an actual product and its minimum being reputation. The traceability axis represents the degree to which the hypothesis's auditability is possible. In such, its maximum would represent a transaction record, and its minimum would be a verbal agreement between two parties.

H1 Intellectual property: Is somewhat traceable and intangible due to various intellectual property strategies ranging from very tangible Patents to intangible trade secrets.

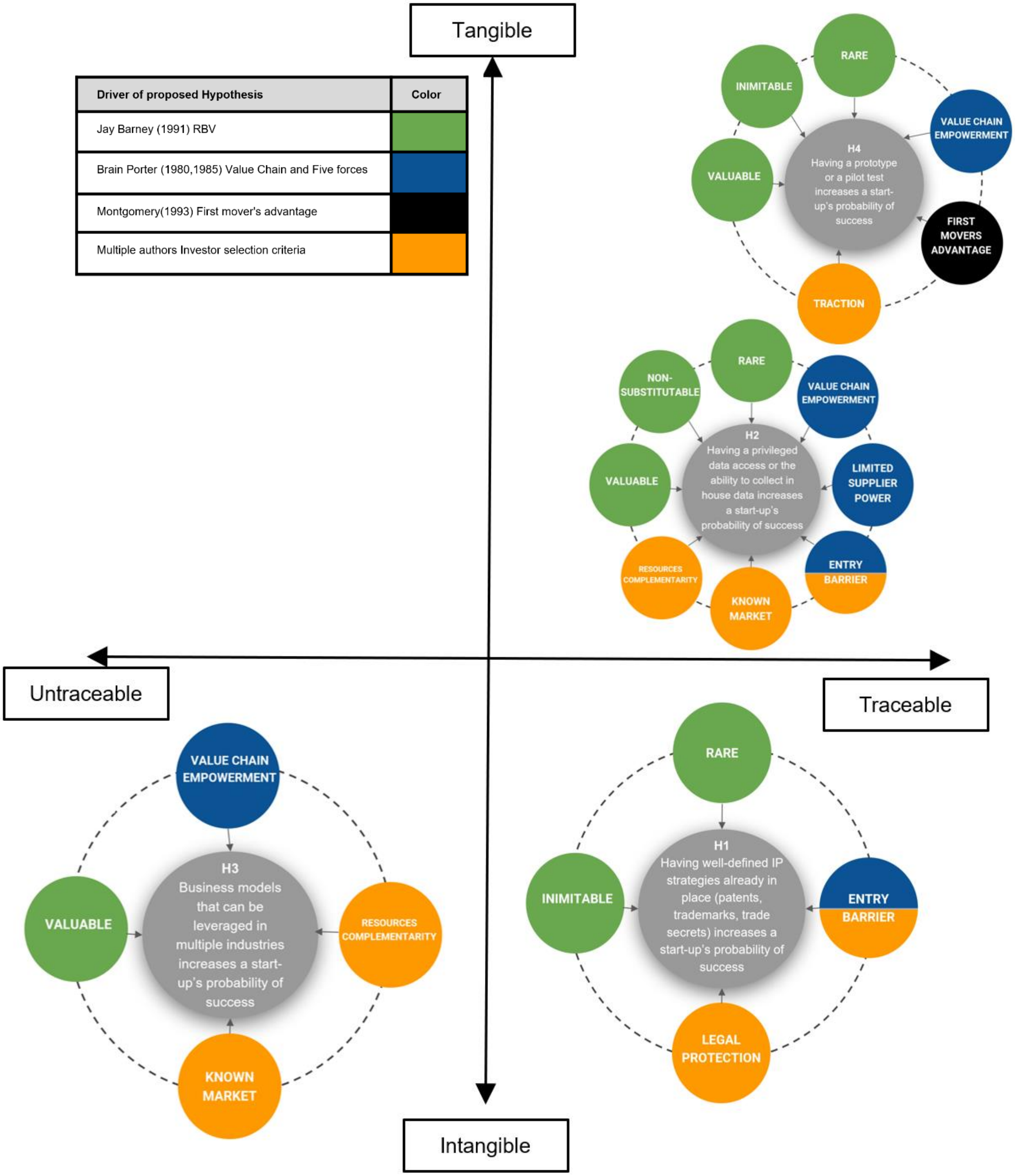
H2 Data access: Is highly traceable and somewhat tangible due to the variety of options for the data collection. From an agreement with a partner with externally collected data being possibly intangible to the self-collected data being very tangible. However, the source of the used data can always be traced back to its source, making it very traceable.

H3 Scope of applicability: Is highly untraceable and intangible due to the multiple other components that must come into play for this concept to hold true.

H4 Prototype: Is considered highly traceable and highly tangible due to its materiality.

This distinction provides an overarching idea of why a venture would progress in an entrepreneurial Program but on broader concepts. This could also be extended to other studies by testing different hypotheses falling within the tangible and traceable axis. Equally, it could also shed light on the importance for a start-up to have or not tangible and traceable assets when starting such a program.

Figure 3.Hypotheses positioning



The following are additional variables that I initially considered analyzing in my preliminary analysis. However, given the focus on technological resources specifically relevant to high tech ventures, I decided not to formalize hypotheses around these but use them as control variables.

3.1.5 Degree of innovation

In the same realm of the technology topic, the degree of innovation within a Start-up in artificial intelligence is an important consideration given its unprecedented reality. However, greater innovation may not always increase the success of a venture. As per Burton et al. (2002), a greater degree of innovation would negatively impact the probability of financing given the complexity of the product and the possible non-familiarity of the investor. However, a lack of innovation would limit differentiation and therefore could expose the venture to an imitability risk, thus harming the investor's interest since the Development risk would be the second most important criterion, according to Astebro (2004).

3.2 Financial resources

Financial resources or the financial health of any enterprise is usually a great indicator of its asset allocation proficiency and business model efficiency. However, unlike established businesses, start-ups are not subject to this reality, especially for ventures that often operate under research and development, most likely non-revenue generating. Nevertheless, key indicators can provide valuable insights for investors.

3.2.1 Revenue

The ability for a venture to generate revenue and hopefully be profitable would be the greatest signal for investors Asterbro (2004) and even supersede the importance of the entrepreneur for Hall & Hofer (1993).

3.2.2 Burn rate

The burn rate is represented in $/month to operate the business and could allow investors to better understand how much time their investment would be fully used under the current operating flow. By a given burn rate value, confident investors who are not seeking a second round of financing may not be interested in providing support due to the utilization rate, which may shortly require additional fundraising.

3.2.3 Runway

The runway is represented in months and expresses how long the business can run until it can no longer support its operations. This could be a great indicator of anticipation skills by the entrepreneurs to seek support, thus providing a positive or negative signal to investors as per what type of individuals they would get involved with if they were to invest.

3.2.4 Investment from other financial players

The bandwagon effect is common in many markets, and investors are no different. Indeed, an investor's interest would increase significantly if other individuals had already boarded the venture, reinforcing the positive signal observed, acting as reassurance in their analysis.

3.2.5 Grants

Even if not in the nature of a classic investment mechanism, support from any organization could be a positive signal for investors since an external entity believed in the start-up's idea and provided funds that could have been allocated to another venture instead.

3.3 Human capital resources

Many deem human capital characteristics a critical criterion in their investment selection. Indeed, the importance of this is expressed by MacMillan (1985), Bachher & Guild (1996), Landstrom (1998), Van Osnabrugge (2000), Sudek (2006), which all rank human capital among the top three most important criteria. Indeed, the essence of the ability to transform an everyday problem into an AI problem using processes, technology, and knowledge, highlights the breadth of skills mobilized in the organization to thrive in this environment. With these skills, they offer a final product that is valued and allows them to access other contracts. This know-how (secret sauce) is often the key differentiator and is usually a sum of intangible and unpatentable interactions that are leveraged in multiple aspects of the venture. This amalgamation of fundamental skills is often seen as core competencies, the essence of competitive advantage, according to Prahalad & Hamel (1990).

3.3.1 Education

The level of education plays a significant role in the degree of innovation (Burton et al. 2002). However, it would not contribute to the investment success of venture capital firms since the most educated founders would direct their strategic vision towards innovation and not an incremental business success and would be more likely to be working in an uncertain sector with very high risk. However, education is considered crucial to human capital quality (Becker 1975) and is recognized as a reassuring parameter to investors.

3.3.2 Experience in relevant field

According to Beckman et al. (2007), the past experiences of founders play an essential role in the future of the start-up and the perception of investors. Moreover, this stems from the "Upper echelon theory" of Hambrick & Mason (1984), who highlighted that the interpretation of situations and the strategic choices of the founders is an expression of their past experiences, their values, and their personality. Experience in the field would positively signal investors since it would reduce investors uncertainty, although it would not be a determinant of investment, simply confirming the right decision (Landstrom 1998).

3.3.3 Number of executive officers

A more significant number of executive individuals who are most probably accountable, having equity invested in the venture, are more likely to be highly invested in solving the problem at hand; thus, a greater number of individuals around a problem increases the odds of success and adequately serving the desired market.

3.3.4 Number of employees

A more significant number of employees could indicate that they have grown to a specific size and that unaccountable individuals, non-equity workers, are willing to work for the business objective and mission.

3.3.5 Management profile

A management team that is balanced in its experience and expertise would be preferred by investors MacMillan (1985). The combination of expertise of the founders in a start-up would bring a plurality of strengths, approaches, and skills that would allow an organization to perceive better the asymmetries of the market that would ensure a sustainable competitive advantage Miller (2002). to be developed with the concept of the structure of the company that encourages this mobility and Oliver's (1997) approach of recognizing opportunities with external conditions, laws, etc. The entrepreneur would be the decisive factor MacMillan (1985) and considered the essential criterion for VCs, SSCs, and angels Bachher & Guild (1996).

3.3.6 Gender of the executive members

The STEM (Science, Technology, Engineering, and Mathematics) sectors are primarily male dominated, with very few women involved in the space. However, in recent years, many industries have seen a growth of women executives, and this sector is not any different. Tracking this status can be insightful information for years to come.

3.4 Location of the Start-up

The company's geographic location seems to be a consideration for investors to ensure validity and proper follow-up of start-ups (Landstrom 1998). In addition, to limit the VCs' time loss, a location near their accountants, lawyers, and any other commonly used services indirectly delimits their investments (Tyebjee & Bruno 1984).

3.5 Age of the start-up

The inception of a venture is often an inspiring and agitated time and is often followed by great uncertainty. However, start-ups' learning curve and learning potential are unlike any other work area and are often done by very few employees. Therefore, the longer a start-up exists, the more it should have learned and have great experiences to leverage in upcoming challenges. Hence, the start-up age is an interesting topic to analyze in such programs.

4 Methodology

In order to test the above hypotheses, I coded the strategic characteristics of 98 AI-focused start-ups that began the CDL-Montreal Program in the two cohorts of 2018-19 and 2019-20, and analyzed the extent to which these strategic characteristics "predicted" the ventures' progress in the Program – as measured by mentors' decisions to "mentor forward" or "drop" a venture.

4.1 Research context: the Creative Destruction Lab at HEC Montreal

The Creative Destruction Lab **(CDL)** is "*a non-profit organization that delivers an objectives-based program for massively scalable, seed-stage, science- and technology-based compani*es". Top universities across the globe in ten key locations host the program with 16 streams of focus ranging from agriculture to fintech, which all leverage emerging technologies. The Program's objective is to empower ventures to successfully raise a Series A round. Since its inception in 2012, CDL has impacted over 500 start-ups and helped them raise well above $4 billion.

HEC-Montreal launched its CDL-Program in 2017, operating it under the school's executive education division (l'École des Dirigeants). For socio-economic development and strategic reasons (tied in part to the Program's reliance on government funding but also, to take advantage of some unique intellectual assets within Montreal's academic and industrial ecosystems), HEC Montreal initially chose to focus its CDL Program exclusively on the development of innovative start-ups that seek to deploy the most recent advances in artificial intelligence technologies. Among other synergies that fostered this choice, Montreal universities were growing top talents with expertise in such technologies, a few high-profile firms mobilizing such technologies were making headways, the government had begun investing heavily in trying to create some sort of industrial cluster around such technologies, and corporate giants like Amazon, Google and Microsoft were beginning to invest in the eventual creation of R&D hubs in the city. Seen in this light, focusing on AI was a natural and synergistic choice at that time.

Like all other programs in the network, CDL-Montreal follows a year-long cycle that begins with the recruitment of potential from late-spring to end of the application season, typically in early August. After evaluating all the applications received by the August deadline, the local team interviews the founders from the top 100 prospects (in late August / early September) and invites the top 50 ventures to take part in the program's two cohorts (of 25 ventures each): one focused on general applications of AI, the other focused on logistics and supply-chain applications.

The objectives-based mentoring program begins in earnest in mid-to-late October, with the first of four local sessions. Each session typically begins with each venture's founders taking part in a series of four "small-group meetings" lasting about 20 minutes each, and where they meet with three or four potential mentors (in each meeting) to discuss some of their current challenges. The discussions then move to a series of moderated "large-room discussions" where the mentors discuss the case of each venture they met and attempt to identify and agree on three objectives that they propose the founders to pursue in the ensuing two months to accelerate their firm's development. Mentors cannot see all ventures; thus, they rely on their colleagues for information. At the end of the day, mentors meet privately to determine, for each venture, if at least one of them sees sufficient potential to mentor that venture forward and devote it four hours of mentoring over the following two months, until the next CDL meeting. Ventures with mentors proceed forward and try to realize their objectives before the next CDL meeting. Ventures without mentors cannot continue and are “dropped” from the program.

Seen in this light, the CDL program offers an interesting opportunity to investigate what seems to explain the forward progression of a venture within the particular context of an entrepreneurial program. By extension, I postulate that such progression reflects in part the collective perceptions of relevant mentors in a technology start-up’s promises.

4.2 Sample frame

Since I began conceiving this study in the Summer of 2020 – a mere few months after the onset of the COVID-19 pandemic and the entire transition of the CDL-Program online, I chose to conduct my study solely on the pre-pandemic cohorts of 2017, 2018 and 2019. Looking at the raw data for the 2017-2018 launch cohort of 25 ventures, however, I discovered that the information collected at the time did not provide accurate and consistent data, raising concerns about the comparability of this cohort with that of other years. After discussing the issues with my adviser, we decided not to retain data from this initial launch year and to focus on all the 100 ventures that had been selected to begin the program in 2018-19 and 2019-20 (50 for each year). Curiously, two ventures invited to start the 2018-19 chose at the last minute not to take part in the Program: this left me with a final sample of 98 ventures for my analyses. [1]

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[1] Please note that consistent with the hypotheses above, my analyses only focus on the ventures that took part in the program – and not those that applied. Though the sample size would be larger if I included all that applied to the program, doing so would be inconsistent with the research’s objectives of measuring performance in the context of the program itself. In addition, the source of the outcome measures would differ, in that selection decisions do not originate from the program’s mentors but from the program’s staff. By strictly focusing on the ventures that began the program, I want to see which ones were selected at each of the four elimination sessions and possibly understand what was common amongst them.

4.3 Outcome variable: venture's progression in the CDL program

To conduct this performance analysis, I documented the ventures' progression in their respective year of the program. For a venture to progress in the program, at least one mentor must provide support for the venture and ensure four hours of their time will be dedicated to help the venture before the next session. Many mentors are ex-entrepreneurs with significant success in selling the venture(s) they had grown. Others are still at the helm of technology ventures they started. And a considerable portion are active investors in funding the development of early-stage start-ups – whether on their own as private business angles or as partners or associate in venture capitalist funds.

Given that the Program unfolds across four sessions (between mid-October and early May the following year) and that for a venture to progress, at least one mentor must "raise a hand" and agrees to commit four-hours of mentoring to that venture, attrition naturally occurs in the Program: some ventures don't make it past the first session, some make it to two or three sessions, and only a few eventually graduate from the program. Table 2 below reports the number of ventures that participated in each year's session. While the numbers do not vary much between the two years (suggesting that mentors showed similar interest for the presented ventures across the two years), variations between each session readily suggest an operationalization for measuring a venture's progression: mentors' decisions to "mentor forward" a venture (or not). Consistent with the above hypotheses, I operationalized the outcome variable for my analyses with a 0/1 dummy code where "1" indicates that mentors had opted to "mentor forward" a venture at a particular session, and "0" indicates their decision not to mentor a venture forward. I created such dummy code for each session of the program.

Table 2.Cohort venture progression per session

Cohort	Session 1	Session 2	Session 3	Session 4
2018-2019	48	33	25	18
2019-2020	50	31	26	20

4.4 Data collection process

4.4.1 Data sources and coding scheme

To obtain valid measures about the strategic factors implied in the above hypotheses, I content-analyzed the applications documents submitted by the entrepreneurs to register their intent to take part in the program. This application summary contained multiple information such as business description, addressed market, grants obtained, founder profile, and much more. To further validate the data, I also content-analyzed the venture information document that the CDL-Montreal staff produced to help the mentors taking part in the first session. These documents contained four sections that were relevant for the hypotheses and other considerations: Venture overview, Product and customer overview, technical overview, and financial overview. By content analyzing these documents, I sought to identity strategic components of the participating ventures that would be relevant for my hypotheses and other strategic considerations. I would use these as predictor variables in analytical models that could explain their progression in the program.

To implement this approach, I began by developing a qualitative coding scheme that would allow me to “bring to light” the ventures’ characteristics (see Figure 4). I developed this coding scheme on the basis of my above review of the strategic management and investors criteria literatures, and through many discussions with my advisers, peers and a blind coder recruited for the project (see below). After a few iterations, the grid consisted of 20 criteria: 4 of these correspond to variables for which I developed specific hypotheses. Whereas the other correspond to control variables and other considerations that I thought might be useful for my analyses.

Figure 4.Full coding scheme for qualitative content analysis

#	Criteria	Description	Scale	1	2	3	4	5	6
1	**Intellectual property**	Does the business own any type of intellectual property which could give them an edge over competitors?	*6*	No patent pending or approved that are relevant in their industry and useful in business operations	Patents are pending approval which are relevant in their industry and useful in business operations	Single patent that is relevant in their industry and useful in business operations	Multiple patents that are relevant in their industry and useful in business operations	Copyrights or trademarks that can be relevant in their industry and useful in business operations	Trade secrets that are relevant in their industry and useful in business operations
2	**Data access**	Who owns the data that powers the artificial intelligence in the business?	*3*	The data is owned by another entity and the start-up has access to these with an agreement (Usually the data was already existent but not fully utilized)	The data is owned by another entity and the start-up has access to these in order to either create or access supplemental data, making it there's as well (Usually a portion of the data was already existent, and the venture modifies it in order to fully utilize it)	The data is collected by the start-up and is owned by them (Usually with the use of sensors)			
3	**Applicability of technology**	Is the venture aligned with an existing market?	*2*	The venture is focused on a target market that is existent	The venture is focused on a target market that is inexistent				
4	**Scope of applicability**	Can the venture transfer their business model or Ai to other markets?	*3*	Same Product/Business on another market	Transferable technology with an altered final product in order to service a different market	Business is addressing a specific and niche which makes any transfer unlikely			
5	**Prototype**	Does the business have an existing prototype or is the business still on the drawing table?	*4*	The prototype is expected to be delivered after the end of the CDL program	The prototype is expected to be delivered before the end of the CDL program	The prototype (MVP) is currently being used but is only available to investors or private use. (Pilot)	The product is currently being used and is available to the public		
6	**Degree of innovation**	How innovative is the product or service offered by the venture?	*5*	The ventures' proposal could be characterized as an optimized Excel spreadsheet	The ventures' proposal suggests a small degree of innovation	The ventures' proposal suggests an average degree of innovation	The ventures' proposal suggests a high degree of innovation	The ventures' proposal suggests a very high degree of innovation and could be a disruptive venture in near future.	
7	**Revenue**	Is this start-up generating revenues, if so, how much? (In thousands and CAD)	*3+n*	The venture is currently in Pre-revenue phase	The venture has very recent revenues but are not solely liked to the venture (ex. they could be from consulting services)	The venture has revenues that are solely linked to the venture Ai utilization. Input amount			
8	**Burn rate**	How much money does this venture utilize on a monthly basis to operate at their current stage? (In thousands and CAD)	*n*						
9	**Runway**	With their current liquidity or credit access, for how long can the venture continue operating before running out of cash? (In Months)	*n*						
10	**Investment from other financial players**	Has the venture previously raised funds?	*5*	No funds have been raised apart from bootstrapping (family, friends and personal)	A convertible note has been given by a financial partner.	An equity investment of 10% or less has been made by an investor	An equity investment of more than 10% has been made by an investor	Series A has been completed	
11	**Grants**	Is the venture benefiting from grants to allow its business to operate?	*4*	No grants have been awarded	One grant has been obtained	Two grants have been obtained	Multiple grants from diverse sources have been awarded		
12	**Education**	What education level represents best the management within the venture?	*4*	Key management individuals have no university level education	Key management individuals have an undergraduate degree	Key management individuals have a master's degree	Key management individuals have a doctoral degree		
13	**Experience in relevant field**	How many years of experience does the executive team cumulate?	*4*	Key management individuals account for no previous years of relevant experience	Key management individuals account for less than 10 years of relevant experience combined	Key management individuals account for 10 to 20 years of relevant experience combined	Key management individuals account for over 20 years of relevant experience combined		
14	**Number of executive officers**	How many executive individuals does the venture account for?	*4*	The venture solely consists of the founder as top management	The venture consists of the founder and a part time partner as top management	The venture solely consists of two cofounder as top management	The venture consists of at least 3 fully involved individuals in the top management		
15	**Number of employees**	As of today, how many individuals embody this venture? Excluding owners	*n*						
16	**Management profile**	Which statement best describe the management's profile?	*5*	The management team solely consists of technical individuals (Doctorates, masters in the field of sciences with the absence of a human science "experts"(MBA or other))	The management team mostly consists of (>50%) of technical individuals (Doctorates, masters in the field of sciences) and consists minorly of human science "experts"(MBA or other))	The management team consists equally of technical individuals (Doctorates, masters in the field of sciences) and individuals in the field of human sciences (MBA or other)	The management team mostly consists of (>50%) of human science "experts"(MBA or other)) and consists minorly of technical individuals (Doctorates, masters in the field of sciences)	The management team solely consists of human science "experts"(MBA or other) with the absence of technical individuals (Doctorates, masters in the field of sciences)	
17	**Quality and review of the venture**	Based on the combination of the strengths and experiences of executive officers, this team could be characterized as…	*5*	Poor	Fair	Good	Very good	Excellent	
18	**Location of Startup**	Where is the start-up located?	*5*	The venture is located in a foreign country outside the North American continent	The venture is located within the North American continent	The venture is located within Canada	The venture is located in Montreal or Quebec	The venture is located in Toronto or Ontario	
19	**Age of Startup**	How many months has passed by since inception until the first round of CDL? (In Months)	*n*						
20	**Gender**	Gender of venture executives	*3*	Male only	Mixed	Female only			

4.4.2 Coding procedures

I content-analyzed all documents in parallel to a second coder (blind to the study's hypothesis) whom I recruited to establish that my coding was not driven by my desire to find support for my hypotheses, but by a reasonably rigorous interpretation of the information at hand. To ensure consistency, I first presented the coding scheme to the blind coder to "train" this person, and answered whatever questions s/he had to validate our common understanding of the coding scheme's descriptions, definitions and operationalizations. To improve the data collection's efficiency and accuracy, I indicated where to usually locate the information in the CDL documents. We adjusted the coding scheme along the way, as part of our initial training discussions.

Having developed a common understanding of the criteria, we began the coding testing phase to assess potential divergences and identify areas for improvement. My supervisor, the blind coder, and I did this exercise in parallel to one another. We did this twice to ensure that we were all consistent and were obtaining similar results. After content-analyzing six different start-ups for training purposes and still obtaining defensible results, we began the independent coding phase of the 92 other start-ups, beginning with all the ventures in the 2018-19 cohort. To limit possible influences, we completed the entire process without discussing any ventures among ourselves. Figure 5 below reports the differences obtained in our coding for the two cohorts. Both years had great overall average coding agreement, with 84% for 2018-2019 and 76% for 2019-2020. As the figure below indicates, a few coding dimensions were considerably divergent in both years – namely Scope of applicability, Degree of innovation, Experience in relevant field, and Quality review of the venture. I noticed a common aspect amongst these dimensions (except experience in relevant field), they are highly subjective and their coding is not sourced directly from a specific section in the documents. To better understand theses differences and to test if disagreement was large (one versus five) or minimal (two versus three), I adjusted the results of the blind coder by one (i.e., a data point coded three would then be transformed to a two or a four). In such, after adjusting theses dimensions the agreement increased drastically as the figure below reports. By doing this adjustment to all coding dimensions with an agreement score below 70%, the overall agreement increased to 92% for 2018-2019 and 89% for 2019-2020.

Figure 5.Grading differences between the two coders

Coding Dimension	**2018-2019**		**2019-2020**	
Technological resources	**Agreement**	**With one grade of adjustment + - 1**	**Agreement**	**With one grade of adjustment + - 1**
Intellectual property	88%		74%	
Data access	80%		64%	90%
Applicability of technology	90%		84%	
Scope of applicability	54%	100%	46%	100%
Prototype	96%		68%	98%
Degree of innovation	40%	84%	20%	74%
Financial resources				
Revenue	100%		100%	
Burn rate	100%		100%	
Runway	100%		98%	
Investment from other financial players	90%		70%	
Grants	98%		74%	
Human capital resources				
Education	98%		84%	
Experience in relevant field	52%	92%	50%	90%
Number of executive officers	76%		82%	
Number of employees	92%		100%	
Management profile	76%		70%	
Quality and review of the venture	40%	86%	40%	82%
Location of the start-up	100%		100%	
Age of the start-up	100%		100%	
Gender of the executives	100%		100%	
Average	**84%**	**92%**	**76%**	**89%**

Overall, the grading results portray a lack of consistent agreement mostly due to subjective coding dimensions but still provide an overall defendable level of agreement (80%). Indeed, when results were misaligned, the coding disagreement was never at the extreme opposites. This suggests that improving the coding scheme by adding greater explanation on the subjective coding dimensions and running through more test coding before the independent coding phase could increase the precision of coders and the study's validity.

After reviewing diverging results, the blind coder and I reviewed all discrepancies and created a final version of all coded ventures for both cohorts of CDL. This process consisted of going over each assigned grade and discussing the best match to truly fit the proposed coding scheme. This final agreed version of the coded ventures was then used as the raw datasets for this study.

4.5 Predictor variables for hypotheses

The following sub-sections describe the operationalizations I developed to "transform" the raw data identified in the above content analyses into defensible "measures" for my model's hypotheses.

4.5.1 Intellectual property

This coding dimension describes the type of intellectual property mobilized by each start-up in the sample. To capture this data, each coder read this question: "Does the business own any type of intellectual property which could give them an edge over competitors?" and selected amongst the following answers:

1) No patent pending or approved that are relevant in their industry and useful in business operations

2) Patents are pending approval which are relevant in their industry and useful in business operations

3) Single patent that is relevant in their industry and useful in business operations

4) Multiple patents that are relevant in their industry and useful in business operation

5) Copyrights or trademarks that can be relevant in their industry and useful in business operations

6) Trade secrets that are relevant in their industry and useful in business operations

Table 3 below reports the distribution of coded instances in the data. The table reveals that trade secrets were the most common intellectual property characteristics of start-ups for both years.

Table 3.Distribution of intellectual property

Cohort	No patent pending	Patents are pending	Single patent	Multiple patents	Copyrights or trademarks	Trade secrets
2018-2019	3	11	0	7	2	25
2019-2020	10	11	5	2	3	19
Total	13%	22%	5%	9%	5%	45%

To test H1ab, I created two contrast codes. The first code allows for testing H1a; it distinguishes firms that did not mobilize any form of IP strategy and those that did. The second code allows for testing H1b by distinguishing firms that mobilize formal IP strategies (patents, whether pending or multiple) and informal strategies (copyrights, trademarks and trade secrets). Table 4 reports the operationalization of these two contrast codes, along with the distribution of cases across the sample.

Contrast Any IP distinguishes ventures that mobilize any form of intellectual property protection (2,3,4,5,6) together versus none (1). For its part, Contrast Patent IP distinguishes ventures that mobilize formal forms of intellectual property protection – namely, patents at any stage of completion (2,3,4) together versus informal forms intellectual property, such as trade secrets and copyrights (5,6)

Table 4.Intellectual property contrast code coefficients and distributions

<table>
<tr><th></th><th>Contrast Any IP</th><th>Frequency</th><th>Percent</th><th>Contrast Patent IP</th><th>Frequency</th><th>Percent</th></tr>
<tr><td>No patent pending</td><td>-2</td><td>13</td><td>13%</td><td>0</td><td>NA</td><td>NA</td></tr>
<tr><td>Patents are pending</td><td rowspan="5">1</td><td rowspan="5">85</td><td rowspan="5">87%</td><td rowspan="3">1</td><td rowspan="3">36</td><td rowspan="3">42%</td></tr>
<tr><td>Single patent</td></tr>
<tr><td>Multiple patents</td></tr>
<tr><td>Copyrights or trademarks</td><td rowspan="2">-1</td><td rowspan="2">49</td><td rowspan="2">58%</td></tr>
<tr><td>Trade secrets</td></tr>
<tr><td></td><td>Total</td><td>98</td><td>100%</td><td>Total</td><td>85</td><td>100%</td></tr>
</table>

4.5.2 Type of data access

This coding dimension identifies the type of data access and possible ownership by the start-up. The grader read this question “Who owns the data that powers the artificial intelligence in the business?” and selected amongst the following answers:

1) The data is owned by another entity and the start-up has access to these with an agreement (Usually the data was already existent but not fully utilized)

2) The data is owned by another entity and the start-up has access to these in order to either create or access supplemental data, making it theirs as well (Usually a portion of the data was already existent, and the venture modifies it in order to fully utilize it)

3) The data is collected by the start-up and is owned by them (Usually with the use of sensors)

As Table 5 below illustrates, ventures tend to prefer having some form of ownership over the data they mobilized in their AI models (82%).

Table 5.Distribution of data ownership

Cohort	Data is owned by another entity	Data is externally owned but internally augmented	Data is internally collected	Not applicable
2018-2019	8	22	18	0
2019-2020	8	20	20	2
Total	16%	43%	39%	2%

To test H2ab, I created two contrast codes. The first code allows for testing H2a; it distinguishes firms that use public data and those that had a form of ownership over the used data. The second code allows for testing H2b by distinguishing firms that internally collect their own data and start-ups that use external data which they augment or modify in order to use it in their algorithms. Table 6 reports the operationalization of these two contrast codes, along with the distribution of cases across the sample.

Contrast Some Data distinguishes ventures that mobilize data which is somewhat owned (2 and 3) together versus public data (1). For its part, Contrast Owned Data distinguishes ventures that outright own data (3) versus ventures that augment external data to their own needs (2).

Table 6.Data access contrast code coefficients and distributions

	Contrast Some Data	**Frequency**	**Percent**	**Contrast Owned Data**	**Frequency**	**Percent**
Data is owned by another entity	**-2**	16	17%	**0**	*NA*	*NA*
Data is externally owned but internally augmented	**1**	80	83%	**-1**	42	72%
Data is internally collected				**1**	16	28%
	Total	96	100%	**Total**	58	100%
	Missing	2		**Missing**	2	

4.5.3 Scope of applicability

This coding dimension identifies the degree of feasibility, if any, that a start-up could transfer their current business model to another market. The grader read this question "Can the venture transfer their business model or Ai to other markets?" and selected amongst the following answers:

1) Same Product/Business on another market
2) Transferable technology with an altered final product in order to service a different market
3) Business is addressing a specific and niche, making any transfer unlikely

As the table below illustrates, the distribution of ventures regarding the applicability of their business model and AI technology is mostly focused (46%) on a niche market with an unlikely transfer.

Table 7.Distribution of scope of applicability

Cohort	**Directly**	**Yes, with adjustments**	**Unlikely**
2018-2019	12	11	25
2019-2020	16	14	20

Total	29%	26%	46%

To test H3ab, I created two contrast codes. The first code allows for testing H3a; it distinguishes firms that can transfer their operations (Directly and after adjustments) and those that cannot(unlikely). The second code allows for testing H2b by distinguishing firms that can transfer directly their operations versus after a few adjustments. Table 7 reports the operationalization of these two contrast codes, along with the distribution of cases across the sample.

Contrast Adapt Possible distinguishes ventures that can be transferred to additional market (1 and 2) together versus niche market unlikely (3). For its part, Contrast Adapt Direct distinguishes ventures that can directly be leveraged on another market (1) versus ventures that need to adjust their offering prior to transfer (2).

Table 8.Applicability of the technology contrast code coefficients and distributions

	Contrast Adapt possible	Frequency	Percent	Contrast Adapt direct	Frequency	Percent
Directly	**1**	53	54%	**1**	28	53%
Yes, with adjustments	**1**			**-1**	25	47%
Unlikely	**-2**	45	46%	**0**	NA	NA
	Total	98	100%	**Total**	53	100%

4.5.4 Product status

This coding dimension identifies the state of development of the start-up' proposed solution regarding its general availability. The grader read this question "Does the business have an existing prototype or is the business still on the drawing table?" and selected amongst the following answers:

1) The prototype is expected to be delivered after the end of the CDL program
2) The prototype is expected to be delivered before the end of the CDL program
3) The prototype (MVP) is currently being used but is only available to investors or private use. (Pilot)

4) The product is currently being used and is available to the public

As the table below illustrates, most if not all ventures in the program have a prototype in working condition for investors to use. This state of development of these start-ups is aligned with the objective of the program.

Table 9.Distribution of product status

Cohort	Prototype delivered after CDL	Prototype delivered during CDL	Prototype is available to investors	Product is available to public
2018-2019	2	2	32	14
2019-2020	0	3	30	17
Total %	2%	5%	62%	31%

To test H4ab, I created two contrast codes. The first code allows for testing H4a; it distinguishes firms that deployed a product or pilot versus other status. The second code allows for testing H2b by distinguishing firms that hold a product used by the public versus a pilot test available to investors. Table 10 below reports the operationalization of these two contrast codes, along with the distribution of cases across the sample.

Contrast Deployed distinguishes ventures that have a usable prototype (3 and 4) together versus ventures with an underdeveloped prototype (1 and 2) together. For its part, Contrast UsedVSpilot distinguishes ventures with a used product by the public (4) versus pilot available to investors (3).

Table 10.Prototype status contrast code coefficients and distributions

<table>
<tr><th></th><th>Contrast Deployed</th><th>Frequency</th><th>Percent</th><th>Contrast UsedVSpilot</th><th>Frequency</th><th>Percent</th></tr>
<tr><td>Prototype delivered after CDL</td><td rowspan="2">-2</td><td rowspan="2">7</td><td rowspan="2">7%</td><td rowspan="2">0</td><td rowspan="2">NA</td><td rowspan="2">NA</td></tr>
<tr><td>Prototype delivered during CDL</td></tr>
<tr><td>Prototype is available to investors</td><td rowspan="2">1</td><td rowspan="2">91</td><td rowspan="2">93%</td><td>-1</td><td>61</td><td>67%</td></tr>
<tr><td>Product is available to public</td><td>1</td><td>30</td><td>33%</td></tr>
<tr><td></td><td>Total</td><td>98</td><td>100%</td><td>Total</td><td>91</td><td>100%</td></tr>
</table>

4.6 Control variables

Based on the four presented hypothesis, the following variables acted as control variables to explain the studied criteria.

4.7 Human capital resources

4.7.1 Level of education within management team

This coding dimension identifies the level of education of the start-up's management team. The grader read this question "What education level best represents the management within the venture?" and selected amongst the following answers:

1) Key management individuals have no university level education
2) Key management individuals have an undergraduate degree
3) Key management individuals have a master's degree
4) Key management individuals have a doctoral degree

As the table below illustrates, most if not all ventures have attended university and over half of managers hold at least a master's degree. With the technicality and innovation level required to be in the AI market, higher education amongst ventures is excepted since they must be accustomed to AI's science, mathematics, and physic-specific content.

Table 11.Distribution of education level

Cohort	No university degree	Undergraduate degree	Master's degree	Doctoral degree
2018-2019	0	10	29	11
2019-2020	2	15	22	11
Total %	2%	25%	51%	22%

In order to leverage this data in the analysis, the data collected was mean centered for a linear trend distribution.

4.7.2 Years of experience in a relevant field

This coding dimension identifies the number of relevant years of experience within the start-up. The grader read this question “How many years of experience does the executive team cumulate?” and selected amongst the following answers:

1) Key management individuals account for no previous years of relevant experience
2) Key management individuals account for less than 10 years of relevant experience combined
3) Key management individuals account for 10 to 20 years of relevant experience combined
4) Key management individuals account for over 20 years of relevant experience combined

As the table below illustrates, very few start-ups consisted of freshly graduated individuals but rather mostly consisted of teams with an accumulated experience of over 20 years.

Table 12.Distribution of the relevant years of experience

Cohort	No previous years of experience	Less than 10 years of experience	Between 10 to 20 years of experience	Over 20 years of experience	N/A
2018-2019	0	14	14	20	0
2019-2020	1	13	15	20	1
Total %	1%	28%	30%	40%	1%

In order to leverage this data in the analysis, the data collected was mean centered for a linear trend distribution.

4.7.3 Management profile

This coding dimension identifies the overall management profile of the start-up regarding their academic background. The grader read this question “Which statement best describe the management’s profile?” and selected amongst the following answers:

1) The management team solely consists of technical individuals (Doctorates, masters in the field of sciences with the absence of a human science "experts"(MBA or other))
2) The management team mostly consisting of (>50%) of technical individuals (Doctorates, masters in the field of sciences) and consists minorly of human science "experts"(MBA or

other))

3) The management team consists equally of technical individuals (Doctorates, masters in the field of sciences) and individuals in the field of human sciences (MBA or other)

4) The management team mostly consisting of (>50%) of human science "experts"(MBA or other) and consists minorly of technical individuals (Doctorates, masters in the field of sciences)

5) The management team solely consists of human science "experts"(MBA or other) with the absence of technical individuals (Doctorates, masters in the field of sciences)

As the table below illustrates, most of the managements' backgrounds were around technical sciences which is understandable given the technicality of the market they are addressing. Being in their beginnings, technology start-ups tend to have mostly, as core members, some individuals who are able of producing a tangible output, AI or coding for instance, hence decreasing the likely hood of having a partner from the human sciences or management studies aboard at this timing.

Table 13.Distribution of management profiles

Cohort	100% Technical	Over 50% Technical	50% Technical and 50% Human science	Over 50% Human science	100% Human Science
2018-2019	21	16	8	4	1
2019-2020	19	13	11	5	2
Total %	40%	29%	19%	9%	3%

In order to leverage this data in the analysis, the data was transformed from (1, 2, 3, 4, 5) into (-2, -1, 0, 1, 2) so the 0 would represent a mixed management profile.

4.7.4 Number of executives

This coding dimension identifies the number of executives involved in the management of the start-up as a proxy for its size. The grader read this question:" How many executive individuals does the venture account for?" and selected amongst the following answers

1) The venture solely consists of the founder as top management

2) The venture consists of the founder and a part time partner as top management

3) The venture solely consists of two cofounder as top management

4) The venture consists of at least 3 fully involved individuals in the top management

As the table below illustrates, over 50% of all ventures consisted of a start-up with two co-founders and 35 % had at least 3 full time individuals working as management. The previous portrays that the typical start-up is more a team project than a solo project.

Table 14.Distribution of number of executives

Cohort	Only founder	Founder and a part-timer	Two co-founders	At least 3 full timers
2018-2019	2	4	24	18
2019-2020	4	2	28	16
Total %	6%	6%	53%	35%

In order to leverage this data in the analysis, I regrouped ventures identified as 1 or 2 together to portray start-ups with only one full-time individual. I recentered the new grading to their sample mean for a linear distribution

4.7.5 Number of employees

This coding dimension identifies how many individuals were employed in the start-up in order to allow it to operate at its current state, indirectly it is a proxy for the size of the organisation and possibly an indicator of their growth stage. The grader read this question: " As of today, how many individuals embody this venture? Excluding owners"? and inputted their answer

1) Input number of employees

As the table below illustrates, most of the ventures employed at least 1 individual and very few consisted of either any employee or more than ten. The most common employee size however in both cohorts was 0 which was the case for 18 ventures. Even if they were the most common size, the majority, 65% consisted of 1 to 10 employees working in the venture, the previous portrays that the typical start-up is more a team project than a solo project.

Table 15.Distribution of number of employees

Cohort	0 employee	1 to 5 employees	6 to 10 employees	11 to 15 employees	At least 16 employees
2018-2019	9	19	12	6	2
2019-2020	9	23	10	4	4
Total %	18%	43%	22%	11%	6%

In order to leverage this data, I tried using the raw data which overemphasized the outlying data points. Therefore, I also opted for the LN based mean centered dataset to minimize the outlier bias.

Table 16.Descriptive statistics of raw number of employees and LN transformed

Number of employees statistics					
	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Raw dataset	98	0.00	42.00	5.939	6.362
LN mean centered based	98	-1.00	3.74	1.190	1.267
Valid N (listwise)	98				

4.7.6 Quality review of the top management

This coding dimension identifies if the combination of competencies and experiences from the executive officer to the start-up would be generally considered adequate for their mandate. The grader read this question "Based on the combination of the strengths and experiences of executive officers, this team could be characterized as…" and selected amongst the following answers:

1) Poor
2) Fair
3) Good
4) Very good
5) Excellent

As the table below illustrates, the distribution of ventures regarding their appreciation from the coders as per the competencies of the management vis-à-vis their start-up is mostly on the positive side. Indeed, over 75% of the ventures were graded good, very good or excellent.

Table 17.Distribution of quality review of executive officers

Cohort	Poor	Fair	Good	Very Good	Excellent
2018-2019	1	9	17	16	5
2019-2020	0	13	14	21	2
Total %	1%	23%	32%	38%	7%

In order to leverage this data in the analysis, I recentered collected grading to its sample mean for a linear distribution.

4.7.7 Gender of the executives

This coding dimension identifies the gender of the executives running the start-up. The grader read this question "Is the venture benefiting from grants to allow its business to operate?" and selected amongst the following answers:

1) Male only
2) Mixed
3) Female only

As the table below illustrates, the distribution of ventures regarding their gender of executives is mostly skewed to male-led enterprises. The previous is quite unsurprising given that the technology field is a male dominated industry. Interestingly, when comparing both cohorts we can notice an increase in the number of ventures characterized by mixed executives, suggesting that efforts to de-genderfy specific areas of work is slowly getting across to industries. In this mindset, CDL has put in a place a minority program to encourage everyone to be part of the STEM (Science, technology, engineering, and mathematics) sector.

Table 18.Distribution of gender of executives

Cohort	Male only	Mixed	Female only
2018-2019	43	4	1
2019-2020	34	15	1
Total %	79%	19%	2%

In order to use this data, I created a contrast code to capture the gender of ventures, by regrading Male as 1, Mixed as 0 and Female as -1 to emphasize the impact of solely being lead by women and men.

4.8 Financial resources

4.8.1 Awarded grants

This coding dimension identifies how many, if any, grants were awarded to the start-up. The grader read this question "Is the venture benefiting from grants to allow its business to operate?" and selected amongst the following answers:

1) No grants have been awarded
2) One grant has been obtained
3) Two grants have been obtained
4) Multiple grants from diverse sources have been awarded

As the table below illustrates, the distribution of ventures regarding their amounts of grants awarded varies considerably.

Table 19.Distribution of awarded grants

Cohort	No grants	One grant	Two grants	Multiple grants	N/A
2018-2019	14	14	6	14	0
2019-2020	16	9	6	18	1
Total %	31%	23%	12%	33%	1%

For this control variable I created a dummy coding emphasising no grants to capture differences between ventures with grants and those without any. Contrast Obtained Grant distinguishes ventures that have obtained grants -namely one, two and multiple grants (2,3,4) versus those that have not (1).

Table 20.Awarded grants contrast codes coefficients and distribution

	Grant dummy	Frequency	Percent
No grants	**-0.5**	30	31%
One grant	**0.5**	67	69%
Two grants			
Multiple grants			
	Total	97	100%
	Missing	1	

4.8.2 Obtained financing

This coding dimension identifies what type of financing, if any, did the start-up obtain. The grader read this question "Has the venture previously raised funds?" and selected amongst the following answers:

1) No funds have been raised apart from bootstrapping (family, friends and personal)
2) A convertible note has been given by a financial partner
3) An equity investment of 10% or less has been made by an investor
4) An equity investment of more than 10% has been made by an investor
5) Series A has been completed

As the table below illustrates, the most common financing situation of start-ups in the program was no funds obtained yet. This state of development of these start-ups fits well with the program's objective. Indeed, being aimed at ventures that could be raising series A post-graduation of CDL, it is likely that most applicants would not have raised any significant amount yet.

Table 21.Distribution of obtained financing

Cohort	No funds raised	Convertible debt	Equity investment of less than 10%	Equity investment of more than 10%	Series A
2018-2019	15	7	10	12	4
2019-2020	16	11	12	7	4
Total %	32%	18%	22%	29%	8%

I created a dummy coding emphasizing no funds raised allowed the analysis of this criterion in a logistic regression. The contrast Obtained funding distinguishes all types of funds raised include all grading except no funds raised (2,3,4,5) to no fund raised (1)

Table 22.Obtained financing Dummy coefficients

	Coefficient	Frequency	Percent
No funds raised	**-0.5**	31	32%
Convertible debt			
Equity investment of less then 10%	**-0.5**	69	68%
Equity investment of more then 10%			
Series A			
	Total	98	100%

4.8.3 Runway

This coding dimension identifies how many months the start-up could continue to operate in the same manner before bankrupting. The grader read this question: " With their current liquidity or credit access, for how long can the venture continue operating before running out of cash? (In Months)":

1) Input number of months

Based on the raw data, the average start-up could continue their ongoing operations for nine months before running into financial difficulties, and 66% of all ventures that provided data (91/98) were between 2 to 15 months from financial distress. Equally, the most common runway of the sample was six months, followed by 12 months, then 10. Suggesting the timing of a possible financing was key for many start-ups as the program would last on average 8 months hence without any change to their operations, either by seeking grants or funding, about 50% of start-ups would have run out of funds before the end of the program. To leverage this data, I tried using the raw data, which overemphasized the data points which were outliers. Therefore, I also tested it on an LN based mean centered dataset to minimize the outlier bias

Table 23.Runway descriptive statistics

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Standard Deviation
Raw dataset	91	1.00	48.00	9.132	6.607
LN mean centered based	91	0.00	3.87	2.002	0.672
Valid N (listwise)	91				

4.9 Technological resources

4.9.1 Applicability of the technology

This coding dimension identifies if the technology being leveraged by the start-up is addressing an existent market. The grader read this question "Is the venture aligned with an existing market?" and selected amongst the following answers:

1) The venture is focused on a target market that is existing

2) The venture is focused on a target market that is inexistent

As the table below illustrates, most if not all ventures in the program have a business idea that is aligned with an existing market. Given that the vast majority have an operational prototype, suggesting market fit, this distribution is likely.

Table 24.Distribution of state of addressed market

Cohort	Existing Market	Inexistent Market
2018-2019	42	8
2019-2020	46	4
Total %	88%	12%

I created a contrast code that captures the existence of the addressed market. Contrast Existing MKT distinguishes ventures that operate in an existent market versus and inexistent market.

Table 25.Distribution of existing vs inexistent market

	Coefficient	Frequency	Percent
Existent Market	**0.5**	86	87.8
Inexistent Market	**-0.5**	12	12.2
	Total	98	100.0

4.9.2 Degree of innovation

This coding dimension identifies the level of innovation associated with the business model and technology of the start-up. The grader read this question “How innovative is the product of service offered by the venture?” and selected amongst the following answers:

1) The ventures' proposal could be characterized as an optimized Excel spreadsheet
2) The ventures' proposal suggests a small degree of innovation
3) The ventures' proposal suggests an average degree of innovation
4) The ventures' proposal suggests a high degree of innovation
5) The ventures' proposal suggests a very high degree of innovation and could be a disruptive venture in near future.

As the table below illustrates, most ventures fall within the small degree of innovation and high degree of innovation.

Table 26.Distribution of innovation degree

Cohort	Very small degree of innovation	Small degree of innovation	Average degree of innovation	High degree of innovation	Very high degree of innovation
2018-2019	2	12	9	16	9
2019-2020	1	18	11	12	8
Total %	3%	31%	20%	29%	17%

In order to leverage this data in the analysis, I recentered data to their sample mean for a linear distribution.

4.10 Financial resources

4.10.1 Revenues

This coding dimension identifies the amount of revenues generated if any by the start-up. The grader read this question: "Is this start-up generating revenues, if so, how much (CAD in thousands)"? and selected amongst the following answers

1) The venture is currently in Pre-revenue phase

2) The venture has very recent revenues but are not solely linked to the venture (ex. they could be from consulting services)

3) The venture has revenues that are solely linked to the venture AI utilization. (Input amount)

As the table below illustrates, most of the ventures, 66%, generated less than 100’000$ in revenues and more importantly, 41% of all start-ups were in pre-revenue phase. This state of development of these start-ups is aligned with the objective of the program. This unique distribution of revenues across ventures limits the utility of these results as is since the 2018-2019 cohort generated 191’000$ in revenues with a standard deviation of 256’000 and a median 73’000$. Also, as per the 2019-2020, they generated on average revenues of 332’000$ with a standard deviation of 447’000$ and a median at 143’000$.

Table 27.Distribution of revenues

Cohort	**Pre-revenue**	**Revenues from 1$ to 100’000$**	**Revenues from 100’001$ to 500’000$**	**Revenues from above 501’000$**	**N/A**
2018-2019	24	13	8	2	1
2019-2020	16	12	14	8	0
Total %	41%	26%	22%	10%	1%

To leverage this data, I tried using the raw data which overemphasized the data points that were outliers. Therefore, I also tested it on an LOG10 based mean centered dataset to minimize the outlier bias.

Table 28.Descriptive statistics of revenues on a LN base

Descriptive Statistics					
	N	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**
Raw dataset	98	0.00	1955000.00	160705.959	326979.730
LOG10 based mean centered	98	0.00	6.29	4.107	1.212
Valid N (listwise)	98				

4.10.2 Burn rate

This coding dimension identifies how much money was used to operate at their current state monthly. The grader read this question: How much money does this venture utilize monthly to operate at their current stage? (In thousands and CAD)"?

1) Input amount per month

As the table below illustrates, the average start-up monthly cost of operations was of about 35’235$. Equally, the most common (55/96) runway of the sample was between 1000 and 30000$ per month followed by 30000 to 59000 with (24/96) ventures. Suggesting like the revenue generated criteria, that the distribution of the ventures was concentrated in the mean area with a few outliers which significantly influence the standard deviation due to their large numbers.

Table 29.Burn rate descriptive statistics

Descriptive Statistics					
	N	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**
Raw dataset	96	1000.00	198000.	35235.125	37648.591
LN based mean centered	96	6.91	12.20	9.903	1.194
Valid N (listwise)	96				

In order to leverage this data, I tried using the raw data which overemphasized the data points which were outliers. Therefore, I also tested it on an LN based mean centered dataset to minimize the outlier bias.

4.11 Location

This coding dimension identifies where the start-up was located. The grader read this question “Where is the start-up located?” and selected amongst the following answers:

1) The venture is located in a foreign country outside the North American continent

2) The venture is located within the North American continent

3) The venture is located within Canada

4) The venture is located in Montreal or Quebec

5) The venture is located in Toronto or Ontario

As the table below illustrates, over 50% of all ventures were from Canada and a considerable amount were from the province of Quebec (46%). The previous is unsurprising due to the location of the entrepreneurial program CDL at HEC Montreal and that there are other CDLs programs across the nation.

Table 30.Distribution of location

Cohort	Outside North America	Within North America	Within Canada	Montreal/ Quebec	Toronto/ Ontario
2018-2019	7	11	2	25	3
2019-2020	13	13	1	20	3
Total %	20%	24%	3%	46%	6%

By regrouping categories, I created a contrast code that captures ventures that were located in the province of Quebec and the ones that were not. Contrast Quebec Based distinguishes ventures that were based in Quebec (4) versus all other locations, such as Outside North America, North America, Canada and Ontario (1,2,3 and 5).

Table 31.Distribution of Quebec based ventures vs other locations

	Coefficient	Frequency	Percent
Outside Quebec	**-1**	53	54%
Quebec based	**1**	45	45%
	Total	98	100%

4.12 Age of the start-up

This coding dimension identifies the age of the venture at the beginning of the program. The grader read this question: " How many months has passed by since inception until the first round of CDL? (In Months)":

1) Input number of months

As the table below illustrates, the average start-up was well over 2 years old and 66% of all ventures were created between 10 to 43 months. The most common age was 12 months at 12% followed by 15 and 39 months at 8%. It is worth mentioning that only 11% of ventures were less than 12 months old and that both the minimum value 2 and maximum value 87 only occurred once (1% of data set). In order to leverage this data, I tried using the raw data which overemphasized the data points which were outliers. Therefore, I also tested it on an LN based mean centered dataset to minimize the outlier bias.

Table 32.Start-up age descriptive statistics

Descriptive Statistics					
	N	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**
Raw dataset	98	2.00	87.00	26.561	16.887
LN Based mean centered	98	0.69	4.47	3.085	0.652
Valid N (listwise)	98				

4.12.1 Cohort year

This coding dimension differentiates the cohorts in the analysis. As mentioned in the sub-section 4.7, in the year of 2018-2019 two start-ups withdrew from the program, they were excluded from the research. I created a contrast code that captures the year of the ventures.

Table 33.Year Contrast coefficient and distribution

	Coefficient	**Frequency**	**Percent**
2018-2019	**-0.5**	48	49%
2019-2020	**0.5**	50	51%
	Total	98	100%

4.13 Logistic regression

Given the research's objective and the nature of the data, I used logistic regression techniques to investigate the extent to which a venture's strategic characteristics could increase the likelihood of a venture progressing in the program. By completing all the coding without knowing whether any of the ventures had been mentored forward or not, at any stage in the program, I address concerns of retrospective biases. By the same token, the fact that the explained and predictor variables come from different sources (mentors' decisions vs qualitative coding of venture documents) I alleviate concerns of common-method bias. (Chang 2010 and Spector 2010)

In order to keep the maximum statistical power, I limited the variables included in different models. To facilitate the interpretations, as previously mentioned, I mean centered all continuous variables, and used contrast codes for the categorical variables. Because of this, the reported results correspond to what would otherwise happen for a "typical" venture in the program. After compiling all datasets, I modeled the data of each strategic resources and created a multiplicity of models in SPSS to evaluate the likelihood of progression in CDL by testing all four hypotheses mentioned above.

Given enough variables were present under the human capital resources and the data distribution of the years of experience and the management profile, I excluded them from the datasets and the models. Thus, the following results section I only analyzed and mentioned the 18 selected criteria with their 28 variables (datasets) see Figure 5 below.

Figure 6.Used data sets for analysis

Usage	Data set	Details
		Analyzed technological resources
H1		***Intellectual property***
	(Any IP)	Contrast code of any IP vs no IP
	(Patent IP)	Contrast code of patents vs other IPs
H2		***Data ownership***
	(Some Data)	Contrast code of public vs owned and partially owned
	(Owned Data)	Contrast code of owned vs augmented data
Control		***Applicability of technology***
	(Existing MKT)	Contrast code of existent vs inexistent market
H3		***Scope of applicability***
	(Adapt Direct)	Contrast code of direct additional market vs other
	(Adapt Possible)	Contrast code of transferable vs non-transferable
H4		***Prototype status***
	(Deployed)	Contrast code of deployed products vs other status
	(UsedVSpilot)	Contrast code of pilots used by investors vs pilot products
Control		***Innovation rating***
	(Innovation rating)	Dataset of centered mean values
		Analyzed financial resources
Control		***Revenue generated***
	(Revenue)	Data set of centered mean values
	(RevLOG10)	Data set of revenues transformed in Log 10 base and mean centered
Control		***Burn rate***
	(Burn Rate)	Data set of centered mean values
	Burn rate LN)	Data set of burn rate transformed in LN base and mean centered
Control		***Runway***
	(Runway)	Data set of centered mean value
	(Runway LN)	Data set of runway transformed in LN base and mean centered
Control		***Obtained financing***
	(Obtnd Funding)	Contrast code of no funds raised vs all other types
Control		***Awarded grants***
		Contrast code of any grant vs no grant (Obtnd Grant)
		Analyzed human capital resources
Control		***Number of employees***
	(Emp size)	Data set of centered mean values
	(Emp size LN)	Data set of employee number transformed in LN base and mean centered
Control		***Education Level***
	(Educ Level TMT)	Data set of centered mean values
Control		***Number of executives***
	(Num Executives)	Data set of centered mean values
Control		***Quality of management team***
	(Quality TMT)	Contrast code of start-ups with an excellent review vs good and very good review
Control		***Male-led venture***
	(Male-led)	Contrast code male led ventures vs mixed gender led ventures
		Analyzed location
Control		***Start-up location***
	(Québec-based)	Contrast code of start-up based in Quebec vs other locations
		Analyzed time perspective
Control		***Age of the start-up***
	(Age@CDL)	Data set of centered mean values
	(LN_Age@CDL)	Data set of age of start-up transformed in LN Base and mean centered
Control		***Cohort year***
	(Year)	Contrast code of cohort years

5 Results

5.1 Descriptive Statistics and Correlations

Table 34 reports the descriptive statistics for all the study's variables, whereas Table 35 reports their pairwise correlations. Observations from Table 34 reaffirm the sample's "technological entrepreneurship" nature: upon entering the CDL-Montreal Program, a "median" venture was based outside Québec and about 24-months old; it had two male executives (at least one of which had completed a Ph.D.) and four employees; it had obtained some funding and grants; it was targeting an existing market and was making about 12,500$ of revenues, but it had a burn rate twice as high (25,500$); and it had about 8 months left of runway before it ran out of funds.

Table 34.Descriptive variables of study's variable

Variables	*Mean*	*Median*	*SDEV*	*Kurtosis*	*Skewness*	*Minimum*	*Maximum*	*Count*
1. Innov Rating	3.27	3	1.16	-1.19	0.03	1	5	98
2. Existing MKT	0.38	0.5	0.33	3.55	-2.34	-0.5	0.5	98
3. Male-led venture	0.57	1	0.82	0.00	-1.41	-1	1	98
4. Num Executives	2.26	2	0.60	-0.79	-0.06	1	3	98
5. Quality TMT	3.28	3	0.93	-0.77	-0.11	1	5	98
6. EducLevel TMT	2.93	3	0.74	-0.36	-0.20	1	3	98
7. Québec-based	-0.04	-0.5	0.50	-2.01	0.17	-0.5	0.5	98
8. Age@CDL1(mths)	26.56	24	16.89	1.91	1.34	2	87	98
9. LN_Age@CDL1	3.08	3.18	0.65	0.79	-0.41	0.69	4.47	98
10. Emp Size	5.94	4	6.36	10.14	2.47	0	42	98
11. Emp SizeLN	1.19	1.39	1.27	-0.68	-0.56	-1	3.74	98
12. Revenue	$160,706	$12,500	$326,980	12.91	3.33	$0	$1,955,000	98
13. RevLOG10	4.10	4.10	1.25	1.04	-0.40	-1	6.29	98
14. Obtnd Funding	0.18	0.5	0.47	-1.39	-0.80	-0.5	0.5	98
15. Obtnd Grant	0.19	0.5	0.46	-1.33	-0.84	-0.5	0.5	97
16. BurnRate	$35,235	$25,500	$37,649	6.41	2.28	$1,000	$198,000	96
17. BurnRateLN	9.90	10.15	1.19	-0.15	-0.54	6.91	12.20	96
18. Runway(mths)	9.13	8	6.61	13.14	2.84	1	48	91
19. RunwayLN	2.00	2.08	0.67	1.02	-0.42	0	3.87	91
20. Year	0.01	0.5	0.50	-2.04	-0.04	-0.5	0.5	98
21. Any IP	0.60	1	1.02	2.90	-2.20	-2	1	98
22. Patent IP	-0.09	0	0.93	-1.84	0.19	-1	1	98
23. Some Data	0.49	1	1.11	1.31	-1.80	-2	1	98
24. Owned Data	-0.04	0	0.91	-1.80	0.08	-1	1	98
25. Adapt Possible	-0.38	1	1.50	-2.01	-0.17	-2	1	98
26. Adapt Direct	0.03	0	0.74	-1.14	-0.05	-1	1	98
27. Deployed	0.79	1	0.78	9.62	-3.38	-2	1	98
28. Used vs Pilot	-0.32	-1	0.91	-1.48	0.68	-1	1	98
29. Presented_S2	0.65	1	0.48	-1.61	-0.65	0	1	98
30. Presented_S3	0.52	1	0.50	-2.04	-0.08	0	1	98
31. Presented_S4	0.39	0	0.49	-1.82	0.47	0	1	98

In terms of the study's predictor variables of interest, this "median" venture had some intellectual protection in place but no patents; it had access to relevant data for its AI engine but was not the owner of this data; its product/service could be plausibly adapted for other markets; and though it had begun deploying its technologies, these efforts were still at the working prototype / minimal value product stage.

Among the most noteworthy observations from the pairwise correlations displayed in Table 35, I note that three control variables systematically exhibit larger correlations with the study's dependent variables (of whether a venture was mentored forward in the program and presented at sessions 2, 3 or 4): i) whether a venture was based in Québec, ii) the venture's age when it began the CDL Program, and iii) the venture's revenue. These observations suggest the relevance of retaining these variables for further analyses. However, I immediately remark that whether using raw or transformed data, age and revenue exhibit inter-correlations in the .30-to-.36 range ($p<.01$). Even if evidence suggests that the extent of this multicollinearity remains moderate, including both variables alongside one another in subsequent analyses could undermine my ability to detect the unique influence of each variable. I examine this question further below by reporting in parallel analyses that include either or both variables.

As for the other control variables in the study, I note that they tend to exhibit nil, small or erratic patterns of correlations with the dependant variables of interest. For instance, a variable like a venture's innovativeness ratings exhibits near-zero correlations with the dependent variables, whereas variables like "targeting an existing market" or "a team's highest level of education" exhibit correlations that range from the negative to the positive but without ever attaining magnitudes that would yield p-values below the .05-threshold.

Moreover, many of these other control variables exhibit moderate-to-large correlations with one or more of the more salient influences of venture age and revenue. This is notably the case of achievement variables like having obtained funding or grants, or constraining factors like a venture's burn rate and runway. In line with one's intuitive understanding of the characteristics of growing entrepreneurial ventures that have obtained some preliminary measures of success, evidence from Table 35 suggests that ventures who "made it" past a certain age tend to have been able to raise funds to do so, and to have made sufficient progress to generate revenues; conversely though, they also tend to exhibit higher burn rates. All these observations suggest that including all these variables in my analyses would increase the likelihood of collinearity issues.

Table 35.Pearson's correlations amongst study's variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Innov Rating															
2. Existing MKT	-0.40**														
3. Male-led venture	-0.05	0.03													
4. Num Executives	0.02	0.00	-0.03												
5. Quality TMT	0.06	0.11	-0.06	0.33**											
6. EducLevel TMT	0.14	0.05	0.05	-0.03	0.09										
7. Québec-based	0.14	-0.22*	-0.12	0.14	-0.01	-0.16									
8. Age@CDL1	0.22*	-0.13	0.01	0.02	0.19	-0.01	0.13								
9. LN_Age@CDL1	0.17	-0.11	0.11	0.03	0.22*	-0.04	0.10	0.92**							
10. Emp Size	0.02	0.08	-0.01	0.06	0.17	-0.06	-0.09	0.40**	0.39**						
11. Emp SizeLN	0.05	0.02	0.08	0.07	0.16	-0.15	-0.01	0.32**	0.37**	0.81**					
12. Revenue	-0.06	0.06	-0.10	-0.03	0.11	-0.05	-0.01	0.31**	0.30**	0.51**	0.39**				
13. RevLOG10	-0.18	0.10	-0.13	0.09	0.13	-0.08	-0.14	0.30**	0.36**	0.44**	0.41**	0.66**			
14. Obtnd Funding	0.02	0.01	0.13	-0.15	0.04	-0.07	0.01	0.14	0.14	0.32**	0.43**	0.18	0.14		
15. Obtnd Grant	0.23*	-0.05	0.08	-0.02	0.02	-0.01	0.22*	0.30**	0.33**	0.19	0.15	0.09	0.20*	0.02	
16. BurnRate	-0.02	0.11	0.16	0.03	0.25*	0.08	-0.13	0.24**	0.27**	0.47**	0.49**	0.41	0.28**	0.31**	0.16
17. BurnRateLN	0.00	0.03	0.15	0.03	0.23*	-0.06	-0.03	0.31**	0.34**	0.49**	0.58**	0.39**	0.29**	0.38**	0.17
18. Runway	-0.05	0.16	-0.18	0.00	0.11	0.03	-0.10	0.18	0.11	0.32**	0.08	0.27**	0.22*	0.03	0.01
19. RunwayLN	-0.05	0.19	-0.10	0.07	0.12	0.10	-0.07	0.07	0.00	0.18	0.07	0.24*	0.20*	0.05	-0.09
20. Year	-0.09	0.13	-0.26**	-0.06	-0.04	-0.12	-0.12	-0.03	0.01	0.04	0.00	0.21*	0.31**	-0.01	-0.04
21. Any IP	0.14	-0.05	-0.06	0.12	0.21*	0.00	-0.06	0.19	0.22*	0.05	0.06	0.07	0.08	0.06	0.06
22. Patent IP	0.00	0.00	0.08	0.23*	0.22*	-0.04	-0.04	-0.03	-0.01	0.13	0.24*	0.08	-0.02	0.17	-0.18
23. Some Data	0.03	0.11	-0.15	0.07	0.00	-0.10	0.07	0.08	0.05	0.07	-0.01	0.08	0.05	-0.04	-0.05
24. Owned Data	0.27**	-0.15	0.00	-0.14	-0.17	-0.08	0.18	0.11	0.10	-0.01	0.03	-0.04	0.02	0.09	0.15
25. Adapt Possible	-0.13	0.09	0.07	0.00	-0.10	0.08	-0.05	-0.12	-0.09	0.09	0.11	0.08	0.09	0.03	-0.13
26. Adapt Direct	-0.12	-0.11	0.02	0.09	-0.07	-0.05	0.10	-0.03	0.03	-0.12	-0.05	-0.09	0.05	-0.15	-0.11
27. Deployed	-0.07	-0.10	-0.05	-0.15	0.00	-0.08	-0.06	0.00	0.05	0.19	0.27**	0.10	0.06	0.07	-0.10
28. Used vs Pilot	-0.02	0.14	0.04	0.20*	0.21*	-0.22*	0.03	0.20*	0.23*	0.09	0.13	0.37**	0.48**	-0.04	0.09
29. Presented_S2	0.04	-0.08	-0.07	0.01	-0.11	0.08	0.28**	0.09	0.10	0.08	0.02	0.11	0.11	0.06	0.02
30. Presented_S3	0.04	0.02	-0.15	0.08	0.00	-0.09	0.31**	0.20*	0.22*	0.10	0.08	0.16	0.18	0.09	-0.02
31. Presented_S4	0.00	0.11	-0.09	0.06	-0.08	-0.04	0.19	0.19	0.18	0.12	0.06	0.08	0.18	0.00	-0.03

Note. With a sample size of 98, the p-value of correlations larger than .199 (in absolute value) is smaller than .05 (marked * in the above table); correlations larger than .259 (in absolute value) have a p-value smaller than .01 (marked ** in the above table).

Continued Pearson's correlations amongst study's variables

Variables	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1. Innov Rating															
2. Existing MKT															
3. Male-led venture															
4. Num Executives															
5. Quality TMT															
6. EducLevel TMT															
7. Québec-based															
8. Age@CDL1															
9. LN_Age@CDL1															
10. Emp Size															
11. Emp SizeLN															
12. Revenue															
13. RevLOG10															
14. Obtnd Funding															
15. Obtnd Grant															
16. BurnRate															
17. BurnRateLN	0.80**														
18. Runway	0.02	0.05													
19. RunwayLN	0.06	0.05	0.86**												
20. Year	0.17	0.12	0.15	0.14											
21. Any IP	0.12	0.13	0.09	0.12	-0.20*										
22. Patent IP	0.17	0.16	0.05	0.05	0.01	-0.04									
23. Some Data	-0.12	-0.12	0.00	0.04	-0.01	0.06	0.08								
24. Owned Data	0.20*	0.17	-0.06	0.00	0.05	-0.02	-0.10	-0.02							
25. Adapt Possible	-0.02	0.05	0.02	0.06	0.12	-0.18	-0.09	-0.02	-0.06						
26. Adapt Direct	0.09	0.04	-0.19	-0.16	0.01	0.10	0.02	-0.18	0.20*	0.04					
27. Deployed	0.12	0.09	0.00	0.04	0.05	-0.11	0.19	0.09	0.03	0.14	0.01				
28. Used vs Pilot	-0.02	0.07	0.10	0.19	0.06	0.03	-0.03	0.22*	-0.05	-0.05	0.03	-0.10			
29. Presented_S2	-0.06	0.03	0.09	0.10	-0.07	0.03	-0.10	0.15	-0.01	0.02	0.09	0.05	-0.09		
30. Presented_S3	-0.02	0.10	0.10	0.06	0.00	0.11	-0.16	0.09	-0.04	0.02	0.01	-0.03	0.03	0.76**	
31. Presented_S4	-0.08	0.01	0.18	0.17	0.03	0.13	-0.12	0.08	-0.03	-0.02	0.14	-0.10	0.09	0.58**	0.76**

Note. With a sample size of 98, the p-value of correlations larger than .199 (in absolute value) is smaller than .05 (marked * in the above table); correlations larger than .259 (in absolute value) have a p-value smaller than .01 (marked ** in the above table).

5.2 Ruling out the influence of more specific control variables

To better examine the potential influence of the more salient control variables and select which ones to retain for subsequent statistical tests, Tables 36 and 37 report the results of statistical analyses regarding the influence of a reduced set of seven control variables that each exhibited larger-than-.1 correlations with any of the "presented at session 2, 3 or 4" outcomes of interest. Although this inclusion rule is admittedly arbitrary, it gives me a basis to select the best covariates for my analyses (Becker, 2005). Reflecting the data collection constraints, Table 36 focuses on relationships between predictor data collected before the program's start and the ventures' eventual progression (or not) to subsequent sessions (2, 3 or 4), whereas Table 37 reports analyses that only retain ventures that made it to Session 2 or 3. To account for possible multicollinearity issues, I conduct separate analyses that include age, revenue, and runway separately. All else being equal, for instance, results from Table 37, Model 1a indicate that the odds of an "average" venture to be mentored forward from Session 1 to Session 2 (in the Program) are 2.45:1 (that is, e to the power of the constant .896; p = .027). In other words, a typical venture presented at the program's Session 1 had 2.5 times more "chances" of being coached by at least one mentor and thus being invited for the Program's Session 2 than to be dropped from the Program without such coaching. Interestingly, however, statistically significant evidence for the parameters "based in Québec" (b = 1.231; p =.011) implies that odds of this "average" venture increased to 4.53:1 if it was based in Quebec ($e^{.896+1.231*.5}$), by comparison to odds of 1.32:1 for an "average venture based outside Quebec ($e^{.896+1.231*-.5}$). I can apply the same basic rationale to other parameter estimates in the tables for which analyses yielded estimates that passed below the .05 threshold: when the estimate is positive, it implies that a higher values on that variable imply increased odds of being mentored forward in the program. The opposite applies when the estimate is negative.

Mindful not to restrict my interpretation solely to considerations of statistical significance (Goldfarb and King, 2016), results reported in Tables 36 and 37 provide evidence for retaining four possible control variables: i) targeting an existing market; ii) being based in Québec; iii) the venture's age and iv) its revenue when it applied to the program. The influence of these variables makes intuitive sense from a mentor's standpoint: all else being equal, for instance, the potential of a growing science-based entrepreneurial venture might conceivably be easier to reach when this venture targets an already exiting market, when this venture is older and beyond some initial hurdles or is already generating larger revenues. I return to the apparent Québec bias below.

Table 36. Results of binary logistic regressions examining the effects of a more salient subset of control variables (1)

Model	Model 1a *b (p)*	Model 1b *b (p)*	Model 1c *b (p)*	Model 2a *b (p)*	Model 2b *b (p)*	Model 2c *b (p)*	Model 3a *b (p)*	Model 3b *b (p)*	Model 3c *b (p)*
	Progress from S1 to S2 (n=98 / n=91 for Model 1c)			Progress from S1 to S3 (n=98 / n=91 for Model 2c)			Progress from S1 to S4 (n=98 / n=91 for Model 3c)		
Constant	.896 (.027)	.912 (.025)	.992 (.021)	.115 (.760)	.111 (.765)	.063 (870)	-.723 (.072)	-.707 (.072)	-.824 (.062)
2. Existing MKT	.067 (.929)	-.097 (.898)	-.078 (.922)	.818 (.244)	.554 (.425)	.794 (.282)	1.384 (.074)	1.106 (.144)	1.422 (.101)
3. Male-led vent.	-.222 (.692)	-.012 (.984)	-.287 (.625)	-.743 (.184)	-.425 (.434)	-.804 (.150)	-.627 (.242)	-.342 (.511)	-.596 (.268)
5. Quality TMT	-.329 (.198)	-.314 (.212)	-.254 (.318)	-.161 (.510)	-.093 (.699)	.022 (.927)	-.366 (.142)	-.317 (.202)	-.168 (.506)
7. Québec-based	1.231 (.011)	1.420 (.005)	1.376 (.007)	1.326 (.004)	1.577 (.001)	1.455 (.002)	.861 (.059)	1.101 (.018)	.948 (.045)
9. Age@CDL1$_{(LN)}$	.395 (.283)			.822 (.028)			.789 (.032)		
13. Revenue$_{(LOG10)}$		.317 (.095)			.410 (.032)			.388 (.044)	
19. Runway$_{LN}$			.448 (.214)			.171 (.622)			.540 (.141)
-2 Log likelihood	115.958	114.251	105.947	118.850	119.098	112.509	118.271	118.814	110.765
Cox & Snell R^2	.102	.118	.112	.158	.156	.138	.121	.116	.109
Nagelkerke R^2	.141	.162	.155	.211	.208	.184	.164	.157	.148

Notes: Results of binary logistic regressions conducted on SPSS.

Table 37.Results of binary logistic regressions examining the effect a more salient subset of control variables (2)

Model	Model 4a *b (p)*	Model 4b *b (p)*	Model 4c *b (p)*	Model 5a *b (p)*	Model 5b *b (p)*	Model 5c *b (p)*	Model 6a *b (p)*	Model 6b *b (p)*	Model 6c *b (p)*
	Progress from S2 to S3 (n=64 / n= 60 for Model 4c)			Progress from S2 to S3 (n=64 / n= 60 for Model 5c)			Progress from S3 to S4 (n=51 / n= 47 for Model 6c)		
Constant	1.366 (.023)	1.357 (.022)	1.093 (.059)	-.027 (.951)	-.005 (.991)	-.144 (.766)	.795 (.151)	.857 (.116)	.925 (.149)
2. Existing MKT	1.984 (.062)	1.607 (.099)	1.863 (.072)	1.714 (.045)	1.461 (.076)	1.841 (.050)	1.276 (.197)	1.047 (.303)	1.113 (.315)
3. Male-led vent.	-1.493 (.144)	-1.292 (.220)	-1.476 (.141)	-.689 (.300)	-.519 (.434)	-.890 (.203)	-.072 (.922)	.032 (.967)	-.204 (.798)
5. Quality TMT	.221 (.574)	.302 (416)	.449 (.224)	-.218 (.483)	-.184 (.551)	.023 (.943)	-.512 (.198)	-.510 (.207)	-.336 (.423)
7. Québec-based	1.435 (.075)	1.862 (.037)	1.231 (.106)	.400 (.481)	.693 (.246)	.395 (.498)	-.218 (.771)	-.081 (.915)	-.388 (.633)
9. Age@CDL1$_{(LN)}$	1.425 (.030)			.830 (.077)			.421 (.456)		
13. Revenue$_{(LOG10)}$		.498 (.084)			.290 (.201)			.174 (.596)	
19. Runway$_{LN}$			-.141 (.804)			.594 (.235)			.830 (.164)
-2 Log likelihood	51.331	53.669	53.299	78.385	80.016	73.821	53.871	54.146	47.437
Cox & Snell R^2	.187	.157	.145	.119	.096	.120	.076	.071	.119
Nagelkerke R^2	.295	.247	.224	.160	.129	.162	.112	.105	.176

Notes: Results of binary logistic regressions conducted on SPSS.

I remark however that these control variables' influence is not necessarily systematic. For a variable like "targeting an existing market", for instance, the evidence is not statistically significant that this variable is associated with a venture's progression from Session 1 to any subsequent sessions (that is, when measured against the progression of all 98 ventures in the sample, as in Table 37). Yet when examining a venture's progression from Session 2 to forward (as in Table 55's Models 4 and 5), evidence for this control variable's positive effect is always below the .10 threshold – and passes the.05 threshold in Models 5a and 5c, when considering a venture's progression from Session 2 to Session 4. This evidence suggests that targeting an existing market plays a role in the Program's middle sessions (i.e., for those ventures mentored forward after Session 1 to present at Session 2).

Still looking across Tables 36 and 37, I did not obtain statistically valid evidence for the influence of a venture being led by a male founder or for a venture's top-management team's quality (at least, as measured subjectively by the blind coder and I, see section 4 above).

As noted above, significant evidence for the variable "based in Québec" suggest all else equal, ventures based in Québec would benefit from higher odds of faring well in the Program than their non-Québec counterparts. Many factors could explain this. One could be that a majority of CDL-Montreal mentors are based in Québec and thus, might prefer mentoring ventures that are also closed to "home". Another could be that the Québec-based ventures invited to the Program might already have desirable characteristics: they could exhibit stronger technological achievements due to their anchoring in the Québec AI ecosystem; high local competition for entry in the Program might translate into these ventures being generally more advanced on average; or they might simply be better known to some mentors. Interestingly, analyses suggest that the apparent "bias" towards Quebec-based ventures might be restricted to the Program's first session: while evidence from Table 37 shows that the influence of being based in Quebec is nearly always below the .05-threshold for statistical validity (that is, when considering the progression of all 98 ventures from Session 1 onward), evidence from Table 37 shows that the magnitude of this effect diminishes (and passes above the .05 threshold for statistical significance) as we consider a venture's progression from Session 2 to Session 3 (in Models 4), from Session 2 to Session 4 (in Models 5) and from Session 3 to Session 4 (in Models 6).

As for the influence of a venture's age and revenues, the pattern of results suggests that the variables' positive influence is perhaps most potent in the Program's middle stage. In this regard, evidence from Table 36 shows that estimates for these variables' positive effects are above the .05-threshold when considering a venture's progression from Session 1 to Session 2 (Models 1ab) but passes below the .05-threshold when considering a venture's progressions from Session 1 to Session 3 or 4 (in Models 2ab and 3ab). Similarly, evidence from Table 37 shows that estimates for these variables' positive effects are below the .05-threshold for age (and .084 for revenue) when considering a venture's progression from Sessions 2 to 3 (in Models 4ab) but then rises above the .05-threshold for subsequent progression to Session 4 (in Models 5ab and 6ab).

Lastly, I note that despite correlations above 0.1 with the dependent variables of interest, analyses reported in Tables 36 and 37 did not yield statistically-valid evidence for the influence of a venture's runway – at least when controlling for other variables in the models. I also signal that due to missing variables for seven ventures, including "runway" as a control variable would necessarily reduce the sample size for my hypotheses analyses.

All in all, these results point towards retaining four possible control variables for my subsequent hypothesis tests: i) targeting an existing market; ii) being based in Québec; iii) the venture's age and iv) its revenue when it applied to the program. It is to these analyse that I turn to next.

5.3 Hypothesis-tests: The influence of technological achievements and resources

Tables 38 and 39 report the results of analyses investigated the effects I hypothesized with my model. Following the same kind of approach that I mobilized above, Table 38 concerns the effects of the hypothesized variables on ventures' progression from Session 1 to Sessions 2, 3 and 4 respectively (that is, in Models 7, 8 and 9) whereas Table 39 concerns the effects of these variables on ventures' progression from Session 2 to Sessions 3 and 4 (in Models 10 and 11) and from Session 3 to Session 4 (in Model 12). Distinctions between models labeled 'a', 'b' and 'c' reflect models that include as control age without including revenue (in Models 'a'), revenue without including age (in Models 'b'), and both variables alongside one another (in Models 'c').

Table 38.Results of binary logistic regressions examining the effects of hypothesized variables (1)

Model	Model 7a *b (p)*	Model 7b *b (p)*	Model 7c *b (p)*	Model 8a *b (p)*	Model 8b *b (p)*	Model 8c *b (p)*	Model 9a *b (p)*	Model 9b *b (p)*	Model 9c *b (p)*
	Progress from S1 à S2 (n=98)			Progress from S1 à S3 (n=98)			Progress from S1 à S4 (n=98)		
Constant	.248 (.634)	.178 (.733)	.176 (.736)	-.469 (.353)	-.512 (.314)	-.542 (.291)	-1.159 (.034)	-1.156 (.033)	-1.200 (.029)
2. Existing MKT	.025 (.975)	-.016 (.984)	.017 (.983)	.737 (.314)	.566 (.437)	.694 (.351)	1.165 (.137)	.992 (203)	1.099 (164)
7. Québec-based	1.350 (.010)	1.619 (.003)	1.600 (.003)	1.614 (.002)	1.925 (<.001)	1.907 (<.001)	.953 (.048)	1.180 (.018)	1.147 (.024)
9. Age@CDL1$_{(LN)}$	.445 (.268)		.177 (.675)	.839 (.040)		.616 (.149)	.708 (.077)	.453 (.044)	.530 (.203)
13. Revenue$_{(LOG10)}$		.556 (.018)	.528 (.031)		.600 (.011)	.521 (.031)			.379 (.104)
21. Any IP	.005 (.983)	.023 (.924)	.001 (.996)	.214 (.362)	.244 (.291)	.193 (.414)	.225 (.380)	.243 (.341)	.204 (.429)
22. Patent IP	-.358 (.177)	-.400 (.146)	-.403 (.144)	-.450 (.081)	-.481 (.070)	-.508 (.062)	-.324 (.202)	-.329 (.198)	-.351 (.178)
23. Some Data	.417 (.063)	.461 (.048)	.465 (.046)	.164 (.446)	.190 (.390)	.210 (.349)	.186 (.408)	.219 (.338)	.227 (.325)
24. Owned Data	-.344 (.230)	-.410 (.169)	-.420 (.161)	-.405 (.152)	-.403 (.161)	-.476 (.112)	-.309 (.256)	-.292 (.281)	-.349 (.212)
25. Adapt Possible	.005 (.978)	-.065 (.703)	-.062 (.719)	.046 (.770)	-.020 (.902)	-.009 (.955)	-.045 (.773)	-.088 (.580)	-.086 (.594)
26. Adapt Direct	.451 (.198)	.456 (.205)	.463 (.201)	.107 (.751)	.057 (.867)	.108 (.757)	.590 (.086)	.540 (.113)	.594 (.090)
27. Deployed	.186 (.550)	.138 (.667)	.134 (.671)	.076 (.804)	.045 (.889)	.020 (.948)	-.149 (.610)	-.185 (.535)	-.202 (.495)
28. Used vs Pilot	-.492 (.082)	-.817 (.016)	-.832 (.015)	-.193 (.479)	-.469 (.136)	-.524 (.104)	-.055 (.835)	-.251 (.398)	-.283 (.346)
-2 Log likelihood	109.605	104.814	104.637	114.484	111.539	109.362	114.695	113.547	111.886
Cox & Snell R^2	.159	.199	.200	.195	.218	.236	.152	.162	.176
Nagelkerke R^2	.219	.274	.276	.260	.291	.314	.207	.220	.239

Notes: Results of binary logistic regressions conducted on SPSS.

Table 39.Results of binary logistic regressions examining the effects of hypothesized variables (2)

Model	Model 10a *b (p)*	Model 10b *b (p)*	Model 10c *b (p)*	Model 11a *b (p)*	Model 11b *b (p)*	Model 11c *b (p)*	Model 12a *b (p)*	Model 12b *b (p)*	Model 12c *b (p)*
		Progress from S2 to S3 (n=64)			Progress from S2 to S3 (n=64)			Progress from S3 to S4 (n=51)	
Constant	1.601 (.019)	1.333 (.035)	1.509 (.029)	-.226 (.665)	-.250 (.635)	-.248 (.646)	.675 (.336)	.817 (.252)	.754 (.299)
2. Existing MKT	2.126 (.086)	1.763 (.102)	2.164 (.080)	1.502 (.097)	1.340 (.129)	1.502 (.098)	.965 (.404)	.819 (.467)	1.013 (.382)
7. Québec-based	2.040 (.033)	2.581 (.019)	2.318 (.030)	.420 (.490)	.585 (.359)	.459 (.482)	-.692 (.415)	-.676 (.438)	-.810 (.368)
9. Age@CDL1$_{(LN)}$	1.393 (.031)		1.558 (.053)	.872 (.095)		.846 (.121	.524 (.409)		.611 (.361)
13. Revenue$_{(LOG10)}$		.468 (.186)	.257 (.482)		.179 (.504)	.046 (.869)		-.075 (.850)	-.184 (.657)
21. Any IP	.475 (.195)	.489 (.162)	.462 (.210)	.357 (.232)	.373 (.202)	.352 (.241)	.317 (.416)	.349 (.376)	.349 (.376)
22. Patent IP	-.750 (.119)	-.767 (.104)	-.785 (.114)	-.361 (.283)	-.329 (.313)	-.360 (.286)	-.255 (.573)	-.168 (.700)	-.241 (.596)
23. Some Data	-.620 (.283)	-.420 (.365)	-.605 (.295)	-.145 (.674)	-.080 (.805)	-.138 (.689)	.151 (.699)	.168 (.662)	.124 (.756)
24. Owned Data	-.777 (.139)	-.491 (.330)	-.769 (.150)	-.493 (.179)	-.337 (.326)	-.491 (.182)	-.227 (.614)	-.151 (.729)	-.253 (.580)
25. Adapt Possible	.030 (.920)	-.094 (.746)	-.014 (.963)	-.162 (.423)	-.166 (.418)	-.168 (.423)	-.121 (.636)	-.104 (.686)	-.103 (.691)
26. Adapt Direct	-.420 (.512)	-.498 (.414)	-.409 (.526)	.697 (.124)	.611 (.158)	.698 (.124)	1.332 (.032)	1.235 (.030)	1.341 (.030)
27. Deployed	-----†	-----†	-----†	-----†	-----†	-----†	-----†	-----†	-----†
28. Used vs Pilot	.808 (.120)	.645 (.255)	.640 (.265)	.565 (.119)	.469 (.252)	.530 (.207)	.531 (.296)	.597 (.316)	.679 (.268)
-2 Log likelihood	44.581	48.611	44.097	71.715	74.223	71.688	47.855	48.513	47.657
Cox & Snell R^2	.269	.221	.274	.206	.174	.206	.179	.168	.182
Nagelkerke R^2	.423	.348	.431	.278	.235	.278	.263	.248	.268

Notes: Results of binary logistic regressions conducted on SPSS.

† This factor no longer varied when restricting sample size; to prevent reporting biased results, I took it out of analyses

With respect to **Hypotheses 1A and 1B,** regarding the effects of intellectual protection, results reported across the two tables typically fail to support the hypotheses, with parameter estimate that do not pass the .05-threshold. Of note however, results from Model 8abc yield evidence at the .6 to .8 level (in p values) of a negative effect for having filed patent relative to other forms of intellectual protection (like trade secrets). Though it is just above the threshold of statistical evidence, this negative effect is somewhat counterintuitive: it suggests that in the context of mentoring growing entrepreneurial ventures mobilizing advances in artificial intelligence technologies, CDL-Montreal mentors might have some reserves about ventures that early on, chose to invest in formal means of intellectual protection. Acknowledging that I cannot speculate about the reasons for this counterintuitive finding (or test its replicability in different years / programs), I note that other students could articulate their supervised project or memoire on investigating the importance of different intellectual protection strategies in programs like CDL-Montreal. For the time being, however, my analyses fail to provide support for Hypotheses 1AB.

Hypotheses 2AB concerns the possible influence of building an AI-based venture on having some privileged access to relevant data (whether through a partnership with other businesses / operations that have this data or building a technology that generate this data outright). Evidence from Models 4abc show statistically valid evidence of a positive effect of building a venture on some privileged access to relevant data (H2a). Focusing on Model 7c that controls for the influence of both age and revenue (b =.465; p =.-046), my analyses reveal that all else equal, a Session 1 venture with this privileged access to data had odds of 1.59:1 ($e^{1*.465}$) to be mentored forward to Session 2, whereas a venture without such access only had odds of 0.39:1 ($e^{-2*.465}$) – meaning that it was much less likely to continue in the Program than other ventures. This result support H2's postulate of a positive effect for building an AI-venture on the hard-to-imitate resource of having some privileged access to relevant data. In this regard, however, results from Table 38 and 39 do not yield statistically valid evidence for this effect at subsequent stages of the Program – or for owning the data outright, as postulated in H2b. Though the latter effect's absence of findings could be due to a lack of statistical power (small sample) or limited variance, my analyses suggest that in a mentoring program like CDL-Montreal, the effects of privileged access to data might be limited in time to the initial: mentors might factor that in in the program's initial stages, but after that, their attention might be focused on other venture considerations.

Moving to **Hypotheses 3ab** about the possible influence of a venture's ability to rapidly adapt its offering to other industries, markets or so-called "verticals", evidence is generally above the .05 threshold of statistical significance, thus denying support for the hypotheses. Interestingly, however, results from Models 9a and 9c (in Table 38) and Models 12abc (in Table 39) would suggest that in latter stages of the Program, ventures that are able to directly adapt their offerings to multiple markets might indeed have an advantage. Using evidence from Model 12c ($b = 1.341$; $p =.030$), for instance, the results would suggest that all else equal, a venture able to directly adapt its offering had odds of 3.82:1 of being mentored forward from Session 3 to Session 4 ($e^{1*1.341}$) whereas a venture without this ability only had odds of 0.26:1 ($e^{-1*1.341}$). Although these results lend support to H3b, the fact that they occur only in the Program's latter stage suggest that it might be interesting to examine what mentors might say about their consideration of such adaptability: is this something that rises to prominence when thinking about funding a venture's Series A or B, as it typically occurs with CDL-Montreal ventures in these latter stages of the Program.

Lastly, results from Tables 38 and 39 yield puzzling evidence with **Hypotheses 4ab**'s postulate that ventures that have been able to deploy their offerings in real-world settings are advantaged. On the one hand, I did not obtain evidence for an omnibus effect of having deployed products, whether through pilots uses (H4a): results across line 27 are systematically above the .05-threshold in Table 38, and the absence of variance for this parameter in the reduced-sample analyses in Table 39 excluded this parameter from the analyses. On the other hand, however, evidence from Table 38, Model 7abc point towards a counterintuitive negative effect of venture having its products being used already, relative to only being deployed through pilot tests. Using results from Model 7c, for instance (b =-.832; p =.015), the parameter estimate implies that a venture that has already deployed its products commercially would face odds of being mentored forward of only 0.44:1 ($e^{+1*-.832}$) whereas a venture that has not yet achieved this commercial stage but has deployed some pilot tests would face odds of 2.30:1 ($e^{-1*-.832}$). In practice, this would suggest that CDL-Montreal mentors would prefer to "coach" ventures that have not yet reached a commercial stage. To determine whether this is the case or not, one would need to conduct additional studies in the field. But for the time being, this counterintuitive result works against the hypothesis I postulated. I also note that evidence was not significant for this effect at other stages of the Program.

All in all, then, my analyses only yielded support for one of my hypotheses: H2a's positive effect of building a venture on some privileged access to data. That said, my work also yielded interesting results regarding the potential advantages of non-formal IP strategies (see H1b results above), for the potential advantages of being able to directly adapt one's offering to multiple markets (see H3b above), and for the counterintuitive effects of having reached commercial stages of deployment in CDL-Montral's kind of mentoring program (see H4b above). Before I discuss the importance of these results for my master's thesis, I report below supplementary analyses I conducted to examine whether the hypothesized effects might vary with age and revenues.

6 Supplementary analyses

6.1 Do main effects vary with a venture's age?

6.1.1 Intellectual protection by age

Tables 40 and 41 report the results of supplementary analyses investigating whether the effects of intellectual protection vary with a venture's age (Table 40) and when limiting analyses to those ventures who progressed in the program (Table 41). Though I cannot conclude that intellectual protection has no effect, these analyses did not reveal any statistically valid evidence that formal mechanisms for defending a venture's intellectual property influence decisions to mentor a venture forward in the CDL-Montreal Program.

Table 40.Results of binary logistic regressions examining the varying effects of intellectual property with age

Model	Model 7a	Model 7b	Model 8a	Model 8b	Model 9a	Model 9b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S1 to S2 (n=98)		Progress from S1 to S3 (n=98)		Progress from S1 to S4 (n=98)	
Constant	.699 (.009)	.735 (.010)	-.003 (.992)	.041 (.883)	-.649 (.018)	-.647 (.023)
7. Québec-based	1.255 (.008)	1.246 (.008)	1.330 (.003)	1.310 (.004)	.793 (.070)	.779 (.078)
9. Age@CDL1$_{(LN)}$	.236 (.515)	.273 (.494)	.647 (.081)	.916 (.097)	.509 (.156)	.718 (.181)
21. Any IP	.069 (.757)	.036 (.884(	.203 (.366)	.151 (.535)	.252 (.297)	.221 (.378)
22. Patent IP	-.203 (.398)	-.198 (.410)	-.360 (.130)	-.370 (.122)	-.259 (.264)	-.314 (.194)
41. Any IP*Age		-.111 (.730)		-.307 (.541)		-.110 (.820)
42. Patent IP*Age		-.184 (649)		.326 (.412)		.529 (.184)
-2 Log likelihood	116.940	116.618	118.882	117.726	121.910	119.959
Cox & Snell R^2	.093	.096	.158	.168	.087	.105
Nagelkerke R^2	.128	.133	.210	.223	.119	.143

Notes: Results of binary logistic regressions conducted on SPSS.

Table 41.Results of binary logistic regressions examining the varying effects of intellectual property with age

Model	Model 7a	Model 7b	Model 8a	Model 8b	Model 9a	Model 9b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S2 to S3 (n=64)		Progress from S2 to S4 (n=64)		Progress from S3 to S4 (n=51)	
Constant	1.331 (<.001)	1.654 (.005)	.160 (.607)	.212 (.529)	.961 (.018)	.931 (.023)
7. Québec-based	1.001 (.150)	1.131 (.130)	.103 (.846)	.224 (.687)	-.537 (.442)	-.581 (.421)
9. Age@CDL1$_{(LN)}$	1.200 (.046)	2.167 (.158)	.595 (.177)	.917 (.199)	.189 (.734)	.011 (.991)
21. Any IP	.260 (.368)	-.025 (.976)	.278 (.294)	.243 (.399)	.244 (.461)	.233 (.486)
22. Patent IP	-.551 (.152)	-.427 (.299)	-.214 (.454)	-.250 (.407)	-.003 (.994)	-.090 (.811)
41. Any IP*Age		-1.228 (.408)		-.231 (.724)		.512 (.568)
42. Patent IP*Age		1.056 (.134)		.868 (.086)		.647 (.319)
-2 Log likelihood	54.707	50.827	82.109	78.666	56.674	55.396
Cox & Snell R^2	.143	.194	.066	.115	.024	.048
Nagelkerke R^2	.225	.305	.089	.155	.035	.071

Notes: Results of binary logistic regressions conducted on SPSS

6.1.2 Owning data by age

In similar fashion, Tables 42 and 43 report the results of supplementary analyses investigating whether the effects of data ownership vary with a venture's age (Table 42) and when limiting analyses to those ventures who progressed in the program (Table 43). Though I cannot conclude that data ownership has no effect, these analyses did not reveal any statistically valid evidence that it influences decisions to mentor a venture forward in the CDL-Montreal Program.

Table 42.Results of binary logistic regressions examining the varying effects of data ownership with age

Model	Model 10a	Model 10b	Model 11a	Model 11b	Model 12a	Model 12b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S1 to S2 (n=98)		Progress from S1 to S3 (n=98)		Progress from S1 to S4 (n=98)	
Constant	.643 (.010)	.623 (.014)	.087 (.718)	.085 (.727)	-.528 (.029)	-.517 (.034)
7. Québec-based	1.287 (.007)	1.324 (.007)	1.381 (.003)	1.393 (.003)	.798 (.071)	.799 (.071)
9. Age@CDL1$_{(LN)}$	.275 (.438)	.192 (.648)	.738 (.046)	.792 (.061)	.593 (.095)	.628 (.139)
23. Some Data	.239 (.216)	.237 (.227)	.118 (.551)	.111 (.577)	.119 (.559)	.124 (.542)
24. Owned Data	-.167 (.519)	-.158 (.547)	-.317 (.214)	-.315 (.218)	-.206 (.400)	-.193 (.432)

43. Some Data*Age		.113 (.745)		-.094 (.789)		-.053 (.885)
44. Owned Data*Age		.616 (.139)		.087 (.827)		-.178 (.636)
-2 Log likelihood	115.753	113.291	120.148	120.027	123.368	123.123
Cox & Snell R^2	.104	.126	.147	.148	.074	.076
Nagelkerke R^2	.144	.174	.196	.197	.100	.103

Notes: Results of binary logistic regressions conducted on SPSS.

Table 43.Results of binary logistic regressions examining the varying effects of data ownership with age

Model	Model 10a *b (p)*	Model 10b *b (p)*	Model 11a *b (p)*	Model 11b *b (p)*	Model 12a *b (p)*	Model 12b *b (p)*
Variables	Progress from S2 to S3 (n=64)		Progress from S2 to S4 (n=64)		Progress from S3 to S4 (n=51)	
Constant	1.611 (<.001)	2.284 (.010)	.377 (.222)	.491 (.138)	1.087 (.005)	1.155 (.004)
7. Québec-based	1.019 (.147)	1.223 (.098)	.124 (.815)	.179 (.746)	-.544 (.437)	-.483 (.507)
9. Age@CDL1$_{(LN)}$	1.579 (.020)	2.493 (.038)	.755 (.097)	.868 (.153)	.213 (.701)	-.020 (.980)
23. Some Data	-.119 (.737)	-.601 (.477)	-.047 (.857)	-.031 (.914)	.062 (.839)	.090 (.772)
24. Owned Data	-.585 (.150)	-.670 (.162)	-.244 (.448)	-.174 (.572)	.017 (.961)	.109 (.782)
43. Some Data*Age		-1.259 (.262)		-.327 (.545)		.089 (.905)
44. Owned Data*Age		-.828 (.261)		-.666 (.187)		-.541 (.381)
-2 Log likelihood	55.340	51.821	83.294	81.193	57.157	56.326
Cox & Snell R^2	.135	.181	.048	.079	.014	.030
Nagelkerke R^2	.212	.285	.065	.107	.021	.045

Notes: Results of binary logistic regressions conducted on SPSS.

6.1.3 Adaptability by age

Tables 44 and 45 report the results of supplementary analyses investigating whether the effects of a venture's ease of adapting its AI offering to multiple markets vary with a venture's age (Table 44) and when limiting analyses to those ventures who progressed in the program (Table 45). By and large, most of these analyses did not reveal statistically valid evidence for such effects. Interestingly, however, Model 15ab in Table 45 uncover evidence just outside the p-value threshold of (in this case, p =.051) that when focusing progression from Session 3 to Session 4 (and considering the variable's underlying articulation), having an adaptable offering increases the odds of a venture being mentored forward increase from a sample average of 3.21:1 ($e^{1.165}$) to 8.26:1

($e^{1.165+1*.946}$) – an increase larger than 150%. By contrast, a venture whose offerings are specific to a niche market only have odds of 0.48:1 of being mentored forward ($e^{1.165+-2*.946}$). Interestingly, evidence from Model 15ab does not provide evidence that these results vary further when controlling for possible interactions between adaptability and age.

Table 44.Results of binary logistic regressions examining the varying effects of a venture's product adaptability with age

Model	Model 13a	Model 13b	Model 14a	Model 14b	Model 15a	Model 15b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S1 to S2 (n=98)		Progress from S1 to S3 (n=98)		Progress from S1 to S4 (n=98)	
Constant	.772 (.001)	.814 (.001)	.185 (.418)	.214 (.366)	-.492 (.031)	-.547 (.031)
7. Québec-based	1.236 (.008)	1.267 (.009)	1.295 (.003)	1.317 (.004)	.711 (.100)	.705 (.112)
9. Age@CDL1$_{(LN)}$	.263 (.453)	.404 (.139)	.689 (.052)	.926 (.022)	.588 (.098)	.987 (.032)
25. Adapt Possible	.059 (.694)	.065 (.672)	.076 (.605)	.077 (.606)	-.017 (.906)	-.070 (.651)
26. Adapt Direct	.174 (.571)	.177 (.576)	-.077 (.796)	-.071 (821)	.376 (.213)	.489 (.159)
45. Adapt Possible*Age		.314 (.197)		.422 (.088)		.519 (.053)
46. Adapt Direct*Age		.185 (.721)		.113 (.842)		-.262 (688)
-2 Log likelihood	117.281	115.597	121.838	118.784	122.889	118.677
Cox & Snell R^2	.090	.106	.132	.158	.078	.117
Nagelkerke R^2	.124	.146	.176	.211	.106	.159

Notes: Results of binary logistic regressions conducted on SPSS.

Table 45.Results of binary logistic regressions examining the varying effects of a venture's product adaptability with age

Model	Model 13a	Model 13b	Model 14a	Model 14b	Model 15a	Model 15b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S2 to S3 (n=64)		Progress from S2 to S4 (n=64)		Progress from S3 to S4 (n=51)	
Constant	1.624 (<.001)	1.948 (.004)	.300 (.271)	.265 (.366)	1.165 (.002)	1.125 (.005)
7. Québec-based	1.033 (.137)	.843 (.241)	.022 (.968)	-.095 (.863)	-.769 (.300)	-.936 (.242)
9. Age@CDL1$_{(LN)}$	1.309 (.034)	1.880 (.037)	.704 (.111)	1.086 (.046)	.357 (.523)	.693 (.368)
25. Adapt Possible	.076 (.745)	.304 (.403)	-.095 (.594)	-.116 (.525)	-.109 (.643)	-.172 (.481)
26. Adapt Direct	-.582 (.260)	-1.075 (.275)	.408 (.255)	.496 (.207)	.946 (.051)	1.065 (.038)
45. Adapt Possible*Age		.653 (.196)		.499 (.116)		.447 (.297)
46. Adapt Direct*Age		-.749 (.326)		-.177 (.817)		-.407 (.703)
-2 Log likelihood	56.279	54.207	82.400	79.672	52.455	50.611
Cox & Snell R^2	.122	.150	.061	.101	.101	.133

Nagelkerke R^2	.192	.236	.083	.136	.149	.196

Notes: Results of binary logistic regressions conducted on SPSS.

6.1.4 Having deployed by age

Tables 46 and 47 report the results of supplementary analyses investigating whether the effects of having deployed one's offering in the field (whether through some prototype or paid pilot) vary with a venture's age (Table 46) and when limiting analyses to those ventures who progressed in the program (Table 47). Though I cannot conclude that such deployment has no effect, these analyses did not reveal any statistically valid evidence that it influences decisions to mentor a venture forward in the CDL-Montreal Program. In this regard, however, I notice that my ability to test such effects was reduced in subsequent stages of the program: the surprisingly large coefficients of some parameters in Table 47 suggests that some of the variables in the model had very limited variance. In this particular case, this reflects observations that by Sessions 3 and 4, most ventures remaining in the program already had deployed their products in the field.

Table 46.Results of binary logistic regressions examining the varying effects of a venture's product deployment with age

Model	Model 16a	Model 16b	Model 17a	Model 17b	Model 18a	Model 18b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S1 to S2 (n=98)		Progress from S1 to S3 (n=98)		Progress from S1 to S4 (n=98)	
Constant	.558 (.074)	.549 (.135)	.172 (.578)	.215 (.555)	-.225 (.458)	-.239 (.500)
7. Québec-based	1.297 (.006)	1.184 (.014)	1.265 (.004)	1.215 (.009)	.726 (.093)	.586 (.192)
9. Age@CDL1$_{(LN)}$	.365 (.316)	-.183 (.747)	.710 (.054)	-.027 (.962)	.561 (.118)	-.088 (.873)
27. Deployed	.153 (.581)	.206 (.537)	-.060 (.829)	.040 (.904)	-.266 (.330)	-.206 (.524)
28. Used vs Pilot	-.295 (.247)	-.309 (.241)	-.079 (.750)	-.027 (.918)	.098 (.683)	.145 (.567)
47. Deployed*Age		.651 (.198)		.726 (.152)		.767 (.115)
48. Used vs Pilot*Age		-.301 (.513)		-.866 (.068)		-.492 (.271)
-2 Log likelihood	115.980	112.810	122.020	114.438	123.244	117.727
Cox & Snell R^2	.102	.131	.130	.195	.075	.126
Nagelkerke R^2	.141	.180	.174	.260	.102	.170

Notes: Results of binary logistic regressions conducted on SPSS.

Table 47.Results of binary logistic regressions examining the varying effects of a venture's product deployment with age

Model	Model 16a	Model 16b	Model 17a	Model 17b	Model 18a	Model 18b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S2 to S3 (n=64)		Progress from S2 to S4 (n=64)		Progress from S3 to S4 (n=51)	
Constant	8.322 (.999)	8.253 (.999)	7.534 (.999)	7.413 (.999)	8.070 (.999)	7.942 (.999)
7. Québec-based	.643 (.349)	.713 (.321)	-.191 (.732)	-.196 (.728)	-.900 (.224)	-.894 (.226)
9. Age@CDL1$_{(LN)}$	1.366 (.036)	.293 (1.000)	.888 (.072)	.414 (1.000)	.613 (.334)	.455 (1.000)
27. Deployed	-6.743 (.999)	-6.296 (.999)	-7.151 (.999)	-6.944 (.999)	-6.970 (.999)	-6.854 (.999)
28. Used vs Pilot	.384 (.380)	.597 (.305)	.375 (.236)	.460 (.172)	.343 (.368)	.322 (.413)
47. Deployed*Age		.147 (1.000)		.207 (1.000)		.227 (1.000)
48. Used vs Pilot*Age		-1.594 (.070)		-.516 (.364)		.145 (.836)
-2 Log likelihood	54.093	50.491	76.006	75.188	52.433	52.390
Cox & Snell R^2	.151	.198	.151	.161	.102	.102
Nagelkerke R^2	.238	.311	.203	.218	.150	.151

Notes: Results of binary logistic regressions conducted on SPSS

6.2 Do the main effects vary with a venture's revenue?

6.2.1 Intellectual protection by revenue

Tables 48 and 49 report the results of supplementary analyses investigating whether the effects of intellectual protection vary with a venture's revenue (Table 48) and when limiting analyses to those ventures who progressed in the program (Table 49). Although these results do not reveal statistically valid evidence for a main effect of data ownership, results from Model 19b (Table 49) uncover a synergistic interaction between patent and revenues (b =1.012; p =.023). Given the model's underlying parameters, these results imply that starting from sample average odds of 4.91:1 to be mentored forward between Session 2 and Session 3, a venture with revenues one standard deviation above the mean and that also had a patent saw its odds increased to 17.39:1 ($e^{1.591+1.012(1.25*1)}$). By contrast, a venture with the same revenues but no patent would have odds of 1.39:1 to be mentored forward ($e^{1.591+1.012(1.25*-1)}$).

Table 48.Results of binary logistic regressions examining the varying effects of intellectual property with revenue

Model	Model 19a	Model 19b	Model 20a	Model 20b	Model 21a	Model 21b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S1 to S2 (n=98)		Progress from S1 to S3 (n=98)		Progress from S1 to S4 (n=98)	
Constant	.715 (.008)	.812 (.007)	-.009 (.973)	.051 (.856)	-.669 (.015)	-864.10 (.960)
7. Québec-based	1.425 (.003)	1.451 (.004)	1.596 (<.001)	1.657 (<.001)	.992 (.028)	1.165 (.014)
13. Revenue$_{(LOG10)}$	.280 (.131)	.514 (.060)	.428 (.028)	.607 (.020)	.372 (.050)	953.30 (.960)
21. Any IP	.084 (.700)	.008 (.974)	.246 (.271)	.190 (.438)	.284 (.239)	864.63 (.960)
22. Patent IP	-.205 (.400)	-.219 (.376)	-.366 (.130)	-.369 (.128)	-.261 (.267)	-.256 (.277)
41. Any IP*Rev		-.190 (.420)		-.288 (.199)		-953.06 (.960)
42. Patent IP*Rev		-.269 (.209)		.134 (.513)		.034 (.862)
-2 Log likelihood	115.035	112.340	116.701	114.566	119.842	106.655
Cox & Snell R^2	.111	.135	.176	.194	.106	.219
Nagelkerke R^2	.153	.186	.235	.259	.144	.297

Notes: Results of binary logistic regressions conducted on SPSS.

Table 49.Results of binary logistic regressions examining the varying effects of intellectual property with revenue

Model	Model 19a	Model 19b	Model 20a	Model 20b	Model 21a	Model 21b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S2 to S3 (n=64)		Progress from S2 to S4 (n=64)		Progress from S3 to S4 (n=51)	
Constant	1.234 (<.001)	1.591 (<.001)	.113 (.719)	-15.349 (.000)	.925 (.025)	1.282 (1.000)
7. Québec-based	1.570 (.045)	2.396 (.008)	.404 (.472)	.586 (.334)	-.406 (.567)	-.379 (.628)
13. Revenue$_{(LOG10)}$	.515 (.065)	.563 (.200)	.309 (.161)	23.705 (.997)	.173 (.554)	6.576 (.999)
21. Any IP	.325 (.258)	.382 (.264)	.321 (.225)	15.811 (.997)	.267 (.422)	.008 (1.000)
22. Patent IP	-.552 (.154)	-.925 (.087)	-.202 (.480)	-.248 (.394)	-.002 (.996)	.101 (.797)
41. Any IP*Rev		-.510 (.137)		-23.588 (.997)		-6.700 (.999)
42. Patent IP*Rev		1.012 (.023)		.241 (.299)		-.280 (.412)
-2 Log likelihood	55.282	46.822	81.893	71.496	56.435	49.843
Cox & Snell R^2	.136	.243	.069	.208	.028	.146
Nagelkerke R^2	.213	.382	.093	.281	.042	.215

Notes: Results of binary logistic regressions conducted on SPSS.

6.2.2 Owning data by revenue

In similar fashion, Tables 50 and 51 report the results of supplementary analyses investigating whether the effects of data ownership vary with a venture's revenue (Table 50) and when limiting analyses to those ventures who progressed in the program (Table 51). Although these results do not reveal statistically valid evidence for a main effect of data ownership, results from Model 23 and 24 (Table 50) point toward a negative interaction between data ownership and revenue. Focusing on the progression from Session 1 to Session 3, for instance, Model 23's results do not provide statistically-valid evidence for a venture's revenue or its data ownership – on average. Yet the significant evidence for a negative interaction (b =-.494; p =.027 in Model 23b and Model 24b b =-.441; p =.040) suggests that when it comes to being mentored forward in the CDL-Montreal program, a venture's data ownership could potentially compensate for its lack of revenue. Conversely, a venture's revenue could compensate for the fact that it does not own the data for its AI engine. Interestingly, results from the analyses reported in Table 51 help "locate" these influence in the progression from Session 2 to Session 3 (b =-.662; p =.042), whereas the evidence is not significant for the progression from Session 3 to Session 4 (b =-.128; p =691). This would suggest that mentor's consideration of the data ownership versus revenue trade-off might be most salient in the program's second session.

Table 50.Results of binary logistic regressions examining the varying effects of data ownership with revenue

Model	Model 22a	Model 22b	Model 23a	Model 23b	Model 24a	Model 24b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S1 to S2 (n=98)		Progress from S1 to S3 (n=98)		Progress from S1 to S4 (n=98)	
Constant	.667 (.008)	.667 (.009)	.100 (.680)	.118 (.636)	-.522 (.032)	-.532 (.038)
7. Québec-based	1.441 (.004)	1.470 (.003)	1.627 (<.001)	1.854 (<.001)	1.020 (.026)	1.281 (.010)
13. Revenue$_{(LOG10)}$	.282 (.132)	.239 (.281)	.431 (.022)	.413 (.077)	.378 (.041)	.520 (.034)
23. Some Data	.232 (.234)	.235 (.230)	.109 (.582)	.106 (.600)	.107 (.599)	.112 (.608)
24. Owned Data	-.155 (.549)	-.164 (.527)	-.286 (.260)	-.296 (.255)	-.194 (.430)	-.175 (.487)
43. Some Data*Rev		.028 (.879)		-.038 (.845)		-.250 (.232)
44. Owned Data*Rev		-.104 (.616)		-.494 (.027)		-.441 (.040)
-2 Log likelihood	114.074	113.776	118.758	113.368	121.822	116.029

Cox & Snell R^2	.119	.122	.159	.204	.088	.141
Nagelkerke R^2	.165	.168	.212	.272	.120	.191

Notes: Results of binary logistic regressions conducted on SPSS.

Table 51.Results of binary logistic regressions examining the varying effects of data ownership with revenue

Model	Model 22a	Model 22b	Model 23a	Model 23b	Model 24a	Model 24b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S2 to S3 (n=64)		Progress from S2 to S4 (n=64)		Progress from S3 to S4 (n=51)	
Constant	1.480 (<.001)	1.727 (.002)	.347 (.257)	.918 (.216)	1.080 (.005)	37.241 (.996)
7. Québec-based	1.435 (.049)	1.627 (.028)	.437 (.431)	.599 (.314)	-.424 (.550)	-.592 (.484)
13. Revenue$_{(LOG10)}$	.515 (.053)	.703 (.211)	.323 (.135)	1.274 (.115)	.162 (.580)	38.566 (.996)
23. Some Data	-.114 (.746)	-.215 (.676)	-.029 (.912)	-.582 (.423)	.055 (.858)	-36.056 (.996)
24. Owned Data	-.287 (.419)	-.320 (.415)	-.123 (.664)	-.084 (.772)	.058 (.870)	.069 (.849)
43. Some Data*Rev		-.352 (.502)		-1.138 (.152)		-38.605 (.996)
44. Owned Data*Rev		-.662 (.042)		-.430 (.073)		-.128 (.691)
-2 Log likelihood	57.929	52.736	83.829	75.377	56.997	48.470
Cox & Snell R^2	.099	.174	.040	.159	.018	.169
Nagelkerke R^2	.156	.274	.054	.215	.026	.249

Notes: Results of binary logistic regressions conducted on SPSS.

6.2.3 Adaptability by revenue

Tables 52 and 53 report the results of supplementary analyses investigating whether the effects of a venture's ease of adapting its AI offering to multiple markets vary with a venture's revenue (Table 52) and when limiting analyses to those ventures who progressed in the program (Table 53). By and large, most of these analyses did not reveal statistically valid evidence for the main effects of adaptability variables. Interestingly, however, Model 25b in Table 52 uncover evidence of a synergistic interaction between adaptability and revenue (b =.297; p =.038). These results imply that compared to a sample average odds to be mentored forward of 2.34:1 ($e^{.851}$), a venture characterized with offerings that are possible to adapt to other markets and revenues of one standard deviation above average would see its odds of being mentored forward increase to 6.70:1

($e^{.851+.544*(1.25)+.297*(1.25*1)}$). By contrast, a venture with the same revenues but offerings that are not adaptable would only have odds of 2.20:1, whereas a venture with revenues one standard deviation *below* the mean but adaptable products would have odds of 2.49:1. And a venture with low revenues and difficult-to-adapt product would be unlikely to move forward in the program, with odds of .81:1.

Table 52.Results of binary logistic regressions examining the varying effects of a venture's product adaptability with revenue

Model	Model 25a	Model 25b	Model 26a	Model 26b	Model 27a	Model 27b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S1 to S2 (n=98)		Progress from S1 to S3 (n=98)		Progress from S1 to S4 (n=98)	
Constant	.783 (.001)	.851 (.002)	.181 (.429)	.181 (.449)	-.502 (.029)	-.601 (.019)
7. Québec-based	1.392 (.004)	1.455 (.004)	1.556 (<.001)	1.626 (<.001)	.913 (.041)	.931 (.045)
13. Revenue(LOG10)	.273 (.141)	.544 (.030)	.431 (.023)	.629 (.006)	.372 (.044)	.578 (.009)
25. Adapt Possible	.030 (.844)	.082 (.610)	.028 (.852)	.044 (.770)	-.058 (.696)	-.096 (.539)
26. Adapt Direct	.150 (.626)	.029 (.934)	-.123 (.683)	-.176 (.583)	.339 (.264)	.433 (.217)
45. Adapt Possible*Rev		.297 (.038)		.235 (.067)		.258 (.043)
46. Adapt Direct*Rev		-.496 (.145)		-.213 (.478)		-.260 (.393)
-2 Log likelihood	115.635	109.045	120.221	116.417	121.413	116.684
Cox & Snell R^2	.105	.163	.146	.179	.092	.135
Nagelkerke R^2	.145	.225	.195	.238	.125	.183

Notes: Results of binary logistic regressions conducted on SPSS.

Table 53.Results of binary logistic regressions examining the varying effects of a venture's product adaptability with revenue

Model	Model 25a	Model 25b	Model 26a	Model 26b	Model 27a	Model 27b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S2 to S3 (n=64)		Progress from S2 to S4 (n=64)		Progress from S3 to S4 (n=51)	
Constant	1.472 (<.001)	1.490 (<.001)	.256 (.351)	.163 (.584)	1.138 (.003)	1.055 (.009)
7. Québec-based	1.499 (.044)	1.652 (.037)	.366 (.511)	.405 (.480)	-.583 (.435)	-.593 (.441)
13. Revenue(LOG10)	.532 (.058)	.583 (.101)	.368 (.101)	.518 (.046)	.242 (.434)	.267 (.433)
25. Adapt Possible	-.035 (.882)	-.008 (.974)	-.150 (.409)	-.166 (.372)	-.138 (.568)	-.153 (.524)
26. Adapt Direct	-.485 (.315)	-.536 (.292)	.411 (.252)	.492 (.218)	.943 (.053)	1.034 (.045)
45. Adapt Possible*Rev		.071 (.706)		.184 (.206)		.225 (.290)
46. Adapt Direct*Rev		.341 (.470)		-.032 (.926)		-.129 (.772)

-2 Log likelihood	57.510	56.625	82.174	80.534	52.242	50.771
Cox & Snell R^2	.105	.117	.065	.088	.105	.130
Nagelkerke R^2	.165	.184	.087	.119	.155	.192

Notes: Results of binary logistic regressions conducted on SPSS.

6.2.4 Having deployed by revenue

Tables 54 and 55 report the results of supplementary analyses investigating whether the effects of having deployed one's offering in the field (whether through some prototype or paid pilot) vary with a venture's revenue (Table 54) and when limiting analyses to those ventures who progressed in the program (Table 55). Though I cannot conclude that such deployment has no effect, these analyses did not reveal any statistically valid evidence that it influences decisions to mentor a venture forward in the CDL-Montreal Program. In this regard, however, I remark that my ability to test such effects was reduced in subsequent stages of the program: the surprisingly large coefficients of some parameters in Table 55 suggest that some of the variables in the model had very limited variance. In this particular case, this reflects observations that by Sessions 3 and 4, most ventures remaining in the program already had deployed their products in the field.

Table 54.Results of binary logistic regressions examining the varying effects of a venture's product deployment with revenue

Model	Model 28a *b (p)*	Model 28b *b (p)*	Model 29a *b (p)*	Model 29b *b (p)*	Model 30a *b (p)*	Model 30b *b (p)*
Variables	Progress from S1 to S2 (n=98)		Progress from S1 to S3 (n=98)		Progress from S1 to S4 (n=98)	
Constant	.548 (.087)	.257 (.505)	.142 (.655)	-.052 (.892)	-.259 (.401)	-.326 (.367)
7. Québec-based	1.545 (.002)	1.464 (.004)	1.577 (<.001)	1.527 (.001)	-.965 (.032)	.967 (.036)
13. Revenue$_{(LOG10)}$	.472 (.031)	.265 (.464)	.546 (.013)	.250 (.487)	.438 (.046)	.083 (.807)
27. Deployed	.105 (.712)	.094 (.770)	-.109 (.703)	-.060 (.852)	-.307 (.268)	-.200 (.518)
28. Used vs Pilot	-.543 (.066)	-.785 (.032)	-.320 (.264)	-.463 (.190)	-.107 (.702)	-.101 (.755)
47. Deployed*Rev		.457 (.151(		.446 (.162)		.395 (.197)
48. Used vs Pilot*Rev		.342 (.505)		.146 (.599)		-.087 (.736)
-2 Log likelihood	111.994	108.703	119.088	116.879	121.481	119.398

Cox & Snell R^2	.138	.166	.156	.175	.091	.111
Nagelkerke R^2	.190	.229	.208	.233	.124	.150

Notes: Results of binary logistic regressions conducted on SPSS.

Table 55.Results of binary logistic regressions examining the varying effects of a venture's product deployment with revenue

Model	Model 28a	Model 28b	Model 29a	Model 29b	Model 30a	Model 30b
	b (p)	*b (p)*	*b (p)*	*b (p)*	*b (p)*	*b (p)*
Variables	Progress from S2 to S3 (n=64)		Progress from S2 to S4 (n=64)		Progress from S3 to S4 (n=51)	
Constant	7.938 (.999)	8.276 (.999)	7.336 (.999)	8.165 (.999)	7.951 (.999)	8.952 (.999)
7. Québec-based	1.195 (.099)	1.242 (.088)	.159 (.778)	.339 (.565)	-.655 (.363)	-.455 (.537)
13. Revenue$_{(LOG10)}$	.431 (.149)	-.029 (1.000)	.240 (.361)	-.415 (1.000)	.088 (.814)	-.545 (1.000)
27. Deployed	-6.482 (.999)	-6.153 (.999)	-6.971 (.999)	-6.434 (.999)	-6.817 (.999)	-6.239 (.999)
28. Used vs Pilot	.242 (.612)	.880 (.463)	.294 (.420)	1.609 (.134)	.297 (.528)	1.803 (.208)
47. Deployed*Rev		-.015 (1.000)	7.336 (.999)	-.208 (1.000)		-.273 (1.000)
48. Used vs Pilot*Rev		-.535 (.511)		-1.055 (.132)		-1.204 (.172)
-2 Log likelihood	57.023	56.455	78.622	75.188	53.341	50.558
Cox & Snell R^2	.112	.120	.115	.161	.086	.134
Nagelkerke R^2	.176	.188	.156	.218	.126	.198

Notes: Results of binary logistic regressions conducted on SPSS.

7 Discussion

As a master's level exercise in applied research, this study provides interesting but somewhat inconclusive observations for strategic management and entrepreneurship. By and large, the research shows that some key RBV principles seem to govern the progression of promising start-ups in mentorship programs meant to accelerate the very development and growth of such start-ups. But evidence falls short of supporting other RBV insights.

7.1 Implications from an academic perspective

Firstly, the results do not support either hypothesis H1a or H1b regarding a start-up's early mobilization of intellectual property mechanisms. Indeed, evidence falls above accepted thresholds for either an omnibus effects of any form of intellectual property mechanism (H1a) or for a more fine-grained distinction between tangible patents or intangible copyrights, trademarks and other secret-sauce strategies (H1b). In and of themselves, these results do not align with the extensive research on the importance of patents being a strong investment signal to venture capitalists (Mann and Sager 2007), and the legal protection provided by any formal IP to de-risk investments (Baccher & Guild 1996).

The lack of evidence, might be due to the considerable number of unknowns which the venture will face in its near future, therefore limiting the ability of a mentor/investor to value this resource at its current stage. Indeed, the patents are not assured to hold value in the future following a possible entrepreneurial pivot. The perceptive of value is a key characteristic of this tested criteria, intellectual property. As a matter of fact, when going back to Jay Barney's RBV theory (1991), I note that for a resource such as intellectual property to form the basis of a competitive advantage, it must hold all four attributes of the VRIN Model (Valuable, Rare, Inimitable and Non-substitutable). Since a patent holds all attributes except value by definition, it seems the value of a resource is essential for a competitive advantage to emerge. Indeed, the other attributes (Rare, inimitable and non-substitutable) ensure the sustainability of the competitive advantage versus the creation of the competitive advantage. The value of a resource can be seen on two angles. First, on an external value creation perspective regarding its quantifiable significance on the market usually portrayed in dollars amounts. Second, it can be valued from within the organization as per the efficiency and effectiveness is hold in the business' operations. Under the RBV theory, for a resource to be considered valuable it must answer both by being valuable to the operations of the organization while ensuring it increases the value offered to the end client. Thus, a patent could fall short of truly creating value for a venture in its early stages and therefore generate inconclusive data on the effect of intellectual property on ventures in a program like CDL. With that in mind, to validate this uncertainty surrounding intellectual property impacts on the progression of a start-up, I would recommend that future studies consider mobilizing qualitative interview techniques to meet with mentors to obtain their take on the utility of intellectual property both formal and informal for such young ventures and if its importance fluctuates as the program advances.

Secondly, the results support H2a regarding the positive influence of having access to some privileged data (whether through partnerships with other firms or by generating this data as part of one's operations). However, results are inconclusive regarding H2b's notions that owning data outright confers superior advantages to simply having access to data through partnerships. On an RBV perspective, this is quite surprising given the central part data plays in the creation of value for a start-up in artificial intelligence. Indeed, theoretically the ownership of the data in completeness would fully fit with the attributes of the VRIN framework and thus be a resource to sustain a competitive advantage. Yet, the privileged access to data checks all attributes of the VRIN framework with the caveat of limited control over rarity and inimitability. Given the reliance on partners who could terminate the arrangement or provide their data to competitors, the competitive advantage could potentially be short lived.

However, this privileged data access following an arrangement with external partners is much more aligned with the positioning school than the capacity building school (Jarzabkowski 2006). Likewise, a privileged access would align well with Dyer's (1998) collaborative theory advantage, where two firms can gain a greater advantage by collaborating versus creating the needed resource internally to realize the desired output. Both of these academic trains of though would be much more in sink with a research scope focused on the external analysis of relationships and their guiding forces such as with the Five forces framework by Michael Porter (1980). Nevertheless, in both cases, the preference from investors seems to be to mentor ventures that have data which is not easily accessible by competitors.

Though I do not yet have the data to establish this, I offer the possibility that perhaps, the effect of owning data versus other methods of having access to data (through partnership) might simply be small in magnitude – at least, this early in the development of high-potential AI-based ventures. After all, CDL mentors might take the view that it makes little difference if ventures own the data upon which they are developing their AI algorithm or simply benefit from a privileged access to such data: both routes allow ventures to create a competitive moat around their development efforts, and this may be sufficient at this stage. Seen in this light, it would thus become interesting to investigate if such differences emerged later in the development of AI ventures. For instance, it would be interesting to examine if Series C investors (or later) are more willing to invest in AI-ventures that own the data they are building on, by comparison to investing in ventures that simply have a privileged access to data generated by other firms.

Thirdly, the results do not support either hypothesis H3a or H3b regarding the importance of having a business model which can be adapted to other verticals, whether with some reasonable adaptations (H3a) or directly, without any such adaptations (H3b). The non-support of the over arching hypothesis does not align with Penrose's (1959) transferability of resources theory and the dynamic capabilities concept of Teece (1997).

However, in the later stages of the program the odds of adaptable ventures progressing increased which lead me to believe these notions could be supported only later in CDL. One possibility could be that in the early stages the investors/mentors are getting to know and understand the business models of all the ventures, making it quite difficult to assess the transferability of the model in the early stages versus latter when they truly comprehend the start-ups challenges and realities. Equally, maybe this line of questioning is only seen as relevant by mentors in the last stages of the program and has no link with their assessment ability of the ventures at hand. Unfortunately, at present I do not have the evidence to tell. However, I would recommend that future studies interested in the evolution of mentor's decision rationale over the course of an entrepreneurship program consider mobilizing qualitative interview techniques to meet with mentors soon after their decisions, to better capture their reasoning. Also, by including a coding scheme to be filed out by all mentors after each session addressing the adaptability of the venture's business model, one would be in position to assess their evaluation ability throughout the progression of the sessions.

Fourthly, the results did not support hypothesis H4a regarding the positive effect of having deployed one's product/service "in the field", even as unpaid pilot tests involving minimum-value early-stage prototypes. Therefore, the data lacks evidence to confirm core concepts of the RBV theory with no sign of interest by investors in a first mover advantage in a new market with a deployed product (Montgomery 1988). This also raises a question on the importance of the value of the proposed products (Barney 1991) which logically should the primary focus of early ventures given the value it should generate to potential clients. This discordance with the strategic literature is most probably due to the context of the study which is centered around mentoring and not investment decisions of investors and not the overarching strategic concepts

Curiously, however, tests of H4b revealed a counterintuitive effect whereby ventures who had reached the commercial stage where less likely to be mentored forward that ventures that had deployed their minimum-value products in the field although without having generated sales yet. This finding is a little puzzling. In principle, theory (and practical logic) would suggest that all things equal, mentors would prefer to "support" the development of ventures that are already showing market traction. In the particular context of CDL ventures, however, it could be that such ventures are not only older (see correlations Table 35), but are also so much further along that they might already have a solid board of advisers, alongside with committed mentors. If this were the case, then perhaps CDL mentors would see little value in mentoring them and would prefer devoting their mentoring efforts towards "younger" ventures that have yet to generate sales from their deployment efforts –thus explaining the counterintuitive efforts. In order to validate this counterintuitive hunch, I would recommend that future studies consider mobilizing qualitative interview techniques to meet with mentors soon after their decisions, so as to better capture their reasoning. Alternatively, it might be possible to analyse recordings of deliberations to examine the particular cases mentors' decisions for ventures that have already garnered sales from their products and services.

Lastly, results mobilizing the location data provide some interesting insight. Indeed, the Quebec based start-ups were more likely to progress in the program. This is a common theme amongst studies who suggest that ventures within a location proximity to the investors are more likely to obtain financing (Landstrom 1998, Tyebjee & Bruno 1984).

All in all, the proposed model I developed in this research (based on internal strategic analysis of technological resources of a venture) proves unable to properly explain a venture's progression in an entrepreneurial mentoring program like CDL-Montreal. This may not be a problem with the theory though: it may simply be that the particular context of very-young entrepreneurial ventures intent on bringing to life innovative new products and service mobilizing the most recent advances in artificial intelligence lies outside the boundary conditions where RBV notions are most potent. In other words, the high-levels of uncertainty characterizing such entrepreneurial ventures also come to "color" the applicability of RBV notions – at least from the perspective of mentor's decisions in an accelerator program.

7.2 Start-ups and mentors/investors implications

This research's primary objective was to uncover new insights to help start-ups and investors/mentors increase their likelihood of success (and decrease time lost) when taking part in mentorship / accelerator program. With this in mind, a start-up would increase its chances of progressing in an entrepreneurial program by having a privileged access to data either from a partnership or by creating it themselves. On the investor /mentor side, by allocating greater resources (time) to ventures with privileged data, their success ratio of mentoring ventures in such accelerators should increase.

7.3 Limitations

In this research, the sample size and the collected data certainly limited the validity of the results. Similarly, the validity and precision of the results obtained were highly influenced by the document's data and the coders' ability to extract the accurate information. Also, the lack of perspective and evolution during the program by only coding the ventures at the start, limited depth of analysis over the course of the progression of CDL. In the same mindset, the absence of after graduation data limited considerably the utility of the insights provided here in for ventures seeking fund raising and investors wanting to increase their success ratio with "real life" investments.

As per the sample, by including all CDL locations with AI cohorts – such as CDL-Oxford and CDL-Toronto, the statistical power would be greater. Indeed, with a total of three locations of similar size, the sample size for the study would have reached upward of 300 for the two-year period. With this sample size, the statistical analysis would have been much more powerful statistically speaking. In addition to offer the availability to detect "smaller" effect sizes, this three-location strategy would also have made it possible to examine possible differences between the decision models of different mentors in different cities.

As per the data collected, the entrepreneurs completed the application documents used as input for the study. Therefore, the objectivity of the data used was limited to the authenticity, consistency, and precision of the entrepreneurs. Unsurprisingly, on a few occasions the clarity of the documents varied, therefore compromising the content analysis. Given the agreement discrepancy between the blind coder and I, the coding scheme precision could be optimized and then extended to additional coders to increase reliability of the data. Also, to limit variation, a structured interview could have been realized with all ventures by a trained coder to ensure consistency and authentic data.

As per the lack of progression perspective, it would have been interesting to code and recode ventures as they progressed in the program. Start-ups being very dynamic, things most probably change between sessions and additional data could be analyzed for a greater understanding of the selection process in such a program and the evolution of start-ups. Also, being a multi-stakeholder program where mentors decide the future of start-ups, having a greater understanding of these individuals would have increased the investor /mentors understanding in the program. With a clear portray of present mentors in each location, year, and session, as per their industry focus, title, fund etc., this would have generated interesting results by identify who supported which start-ups and when along the program.

Finally, as per the “real life” utility, no data after CDL for alumni ventures was available. This could have greatly extended the scope of the research. Indeed, by identifying finishing ventures who had successfully raised a Series A or any type of funding, the research could have compared the value of technological resources in a Program versus during the funding stage.

8 Conclusion

In conclusion, even though only one sub-hypothesis was successfully supported, this research provides some interesting light on the factors conducive to succeed in a program like CDL-Montreal. Though these results did not factor heavily in my initial theorizing, I found that the most interesting findings pertained to the few observations reported in Table 39 regarding how different variables might have different impacts at different moments in the program. This suggests that resource allocation from start-ups is immensely time dependent to where and what they are doing versus where they would like to be.

On a personal note, completing this research considerably improved my degree of analysis and comprehension of strategic management and opened my interest in financing complex start-ups. The undertaking of such a project influenced my work ethic and appetite for sizeable data-heavy problems. Although completing this work was no easy task, given my full-time employment in banking throughout the redaction of this memoire, the process empowers me today with the confidence to undertake other sizeable work on a day-to-day basis and other big projects in the future. All the involved parties in this research understood my work-study life balance and were there at the right time to execute and deliver the expected results to make this project move forward. The journey was an actual roller coaster, but with the support of my partner, my family, and friends, I never gave up.

Overall, I found this research project to accurately conclude my studies in strategy while exposing me to the ever-growing world of artificial intelligence.

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