Which start-up teams get funded and why? Skills' level and skills' variety combined effects

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Abstract

Entrepreneurship research suggests that start-up teams' human capital has a signal-quality effect on how easily they can access financial resources. We look at how start-up teams' varied skill sets and varying skill levels impact digital firm fundraising in early phases. This empirical study uses a sample of 498 digital firms, of which 312 have raised. The results show that investors select start-up teams that have either a high level of expertise or a high level of variety of skills, but only some at a time. Furthermore, the amount and speed of funding that start-up teams can secure from investors are negatively impacted by a high level of skills.

Keywords: Entrepreneurship, Fundraising, Start-up Teams, Competencies

JEL Classification: L22, L26, L85

1 Introduction

For regions and countries, digital businesses represent a source of growth (Autio, 2016). Therefore, the conditions of their emergence and growth are of interest to researchers, practitioners, and political decision-makers. This article contributes to this critical agenda by examining the relationship between the human capital of start-up teams evolving in digital markets and the performance of these firms, which we will examine here from the angle of resource access, specifically the first round of risk capital financing from outside investors.

What teams are funded and why they are funded are recurring themes in contemporary economic and entrepreneurial literature (Klein et al., 2020). Knight et al. (2020) defines start-up teams as a group of individuals having the characteristic of being on a continuum of three variables related to ownership, decision-making, and entitativity, and access to external funding is one of the essential factors for fostering their emergence and expansion (Klein et al., 2020). The focus on start-up teams stems from the fact that most entrepreneurial initiatives are run mainly by groups of individuals rather than by lone individuals (Klotz et al., 2014). Because start-up teams frequently need more cash flow to cover the upfront development costs that help to enrich their activities, obtaining external funding is a challenge that cannot be overlooked, especially during the early stages. Early-stage start-up teams focus primarily on the search for a commercially viable idea, which is translated into the selection of a digital business model, which is dependent on the surrounding environment (e.g., systems of data analysis, online communities, cloud computing, etc.) (Nambisan, 2017). From an investor's perspective, investing in an early-stage firm is extremely risky because of the lack of track record of the founding teams or historical financial results. Furthermore, several experiences have shown that it is tough to predict which teams will win (Ghassemi et al., 2015; Duhigg, 2016). Then, to limit information asymmetries, investors carry out their due diligence and base their investment decision on quality-signals (Spence, 1978; Ko and McKelvie, 2018).

Among the immediately available signals, investors examine the competitive environment, the firm's business strategy, and the start-up teams' human capital composition as indicators of future success. Generally speaking, the entrepreneurship literature flexibly defines human capital and includes knowledge and skills (Ngoasong, 2017; Marvel et al., 2016). In this regard, the organizational theory tailored to the context of entrepreneurship proposes that start-up teams' human capital influences firms' processes and operations through the imprinting effect (Packalen, 2007). This fundamental idea describes how the past influences the present and, in the case of start-up teams, how they make it easier to access financial resources. Theorists contend that start-up teams' composition also serves as a signal (Spence, 1974) that investors use to bridge the gap for their lack of understanding of the team members' perceptions of the firm's quality (Plummer et al., 2016). Concretely, investors use data related to start-up teams' human capital because it is direct and easy to access information, such as the demographic characteristics or functional diversity of the teams (Colombo and Grilli, 2005; Beckman et al., 2007; Eddleston et al., 2016)

However, empirical studies suggest that adding more human capital to a start-up team does not necessarily translate into greater success (Pierce and Aguinis, 2013). On the one hand, empirical studies suggest that a certain level of human capital stimulates the discovery of new business opportunities (Shane and Venkataraman, 2000; Marvel et al., 2016), increases the likelihood of developing radically new and commercially viable products (Marvel and Lumpkin, 2007), and increases the odds of securing external funding (Beckman et al., 2007). The rationality of investing time in years of professional experience and education to learn new skills to increase the odds of raising money from investors, however, is called into question (Audretsch and Lehmann, 2004). On the other hand, studies looking at the impact of start-up teams' diverse skill sets have shown that they help find more opportunities (Shane, 2000), solve complex problems (Hong and Page, 2001) and stimulate fundraising (Ko and McKelvie, 2018). However, other studies suggest a trade-off regarding the diversity of skills within start-up teams because too much diversity can result in high transaction costs, such as conflict and tension due to extensive cognitive gaps between individuals (Nooteboom et al., 2007). In conclusion, although the level and diversity of start-up teams' skills have significant implications for the success of firms in their early stages, empirical research has produced conflicting results. Therefore, there is a need for new research on the levels and degrees of variety of start-up teams' skills, particularly in a digital environment where investors draw on digital firms with non-linear revenues. Examining the internal team configurations of digital start-up teams through the lenses of skills is one way to respond to this call.

In this article, we examine the impact of various combinations of skill levels and skill variety of start-up teams that are critical for receiving early funding. Our empirical study is based on a sample of 606 digital firms, 434 of which have raised capital and 172 have not. Following our claims, we find that investors favor start-up teams that have either a high level of competence or a high level of variety of skills, but only at a time. Start-up teams that are comprised of highly skilled individuals in related fields, i.e., when the variety of their expertise is low, receive more financial resources. High levels of expertise, however, harm the amount and speed of funding that start-up teams can secure from investors when their skills are varied.

The article makes several contributions. First, our findings offer fresh avenues for reflection on the composition of start-up teams and the signal generated among investors. Indeed, past empirical studies have long focused on one of the two dimensions of start-up teams' skills. On the one hand, they either focus on their proficiency level, referring to the novice vs. expert, operationally measured by years of experience. On the other hand, they focus on the level of skills' variety, referring to the specialist vs. generalist and operationally measured by the Hirschman or Blau Index). However, when separated, a firm's success is not explained by either of these two dimensions. Furthermore, not only do some levels of skills only apply to some contexts, but certain levels of variety of skills only apply to some contexts. Indeed, the digital context, in contrast to the industrial context, is governed by other social and technological specificities that require different signals. We suggest a methodology in which we assess these two aspects jointly in a digital context. Second, many empirical studies looking at how start-up teams'composition affects investors' evaluations focused on indicators such as education (Franke et al., 2008), entrepreneurial experience (Beckman et al., 2007), industry experience (Becker-Blease and Sohl, 2015), or leadership experience(Hoenig and Henkel, 2015). In this article, we suggest a skill-based approach, i. e. we focus on "outcomes of human capital" (i. e., their knowledge, skills, and abilities) because they are thought to be more accurate and direct indicators than "investment in human capital" measures like education and years of experience (Unger et al., 2011; Marvel et al., 2016).

2 The effects of entrepreneurial teams' skills' level and skills' variety on digital firms' fundraising

Entrepreneurship researchers have extensively explored financing digital firms in recent years (Klein et al., 2020). This literature has discovered, among other things, that start-up teams often exhibit characteristics that signal quality to investors, potentially enabling them to access external funding (Roure and Keeley, 1990; Reese et al., 2020). Such characteristics include the founders' social capital (Shane and Cable, 2002), the team's demographics and size (Eisenhardt and Schoonhoven, 1990), and the founders' functional background (Ensley et al., 1998). In this regard, the recent emphasis on teams rather than single founders is noteworthy because, as acknowledged in the literature, entrepreneurial initiatives are most frequently the result of a team (Klotz et al., 2014). Additionally, this literature has discovered that the strength of task-relevant expertise as a signal of venture quality depends on a variety of variables, including the industry environment (Townsend and Busenitz, 2015), the match with an investor's characteristics (Aggarwal et al., 2015) or the investor's experience (Franke et al., 2008).

For digital firms looking to grow quickly and significantly, the ability of start-up teams to raise capital is crucial during the early stages of development (Rosenbusch et al., 2013). Early on, start-up teams frequently lack the cash flow needed to cover the costs that will later help them develop their technical and commercial activities. In this stage, the start-up teams of digital firms concentrate primarily on searching for an exploitable idea and selecting a coherent digital business model. Getting external funding allows early-stage businesses to surpass the liability of newness and smallness limitations and finance the development of products or services. Even though open-source software tools and cloud computing have proliferated and generally reduced experimentation costs, business founders still incur initial costs.

To create a quality signal and attract investors' attention and hope for access to more financial resources, start-up teams must show investors that they have a strong enough future development potential (Ko and McKelvie, 2018). These early-stage firms' issue is that they need a track record to demonstrate to investors. In light of this, early-stage start-up teams aim to showcase qualities that will inform investors about their ability to serve a market in the future. Investors use a wide range of indicators, including start-up teams' skills as evaluation criteria, to decide whether to invest in a company and how much to invest. Furthermore, an even greater emphasis should be placed on the human capital of start-up teams because, during this stage, a small group of people is responsible for formulating the strategies and carrying them out operationally. The human capital is even more critical because liquidities are scarce, resources are not abundant, and capital is scarce (Beckman et al., 2007).

In this situation, we propose that start-up teams with higher levels of skills have a greater chance of achieving specific entrepreneurial milestones, a greater capacity to persuade investors, and a greater likelihood of attracting capital and investment (Zarutskie, 2010). First of all, start-up teams with higher levels of skills increase their willingness to take risks and their entrepreneurial behavior (Becherer and Maurer, 1999), which ultimately helps them capitalize on business opportunities they come across by taking advantage of them (Shane and Venkataraman, 2000; Chandler and Hanks, 1994). Because of this, start-up teams with higher levels of skills may be better able to manage the operational aspects of their business, especially in a digital environment where the acquired skills help entrepreneurs make use of the available technological tools (Nambisan, 2017). The development of new technologies and radically innovative products can be better understood at a higher level of skills' proficiency to differentiate from the competition (Marvel and Lumpkin, 2007). Second, a high level of skills proficiency is beneficial for an organization's success because it allows for the acquisition of complementary resources and can make up for the lack of financial resources that is a problem for many digital firms in the early stages (Beckman et al., 2007). Finally, developing skills and knowledge is a prerequisite for further entrepreneurial learning and helps business owners acquire additional skills and knowledge that will help their company grow (Hunter, 1986).

Therefore, we propose that a high level of skills within a start-up team enhances the quality of the signal intended for investors looking to engage financially in the early stages. The investors are alarmed by this sign because it suggests that higher skill levels may translate into future success, which should draw early-stage investors.

H1: Start-up teams with greater skill levels will get more fundings from investors

To accurately examine the impact of start-up team skills on the future success of a digital firm, we must examine not only the level of the skills but also the variety of these skills because they are at the heart of the dynamics of start-up teams in the early stage phases (Grillitsch and Schubert, 2021). Indeed, the success of entrepreneurial ventures is frequently the result of collaborations rather than solitary initiatives, necessitating the combination of knowledge, the synergy of skills, and, consequently, the involvement of multiple individuals.

Empirical studies support the idea that multiple forms of diversity and organizational performance positively (Zhou and Rosini, 2015). According to the literature, there are two types of diversity: surface-level differences (e.g., race, ethnic origin, age, etc.), and deep differences (e.g., education, skills, capacities, attitudes and personalities) (Bell, 2007). For instance, empirical studies suggest that the diversity of educational background within a firm's management team contributes a wide range of skills and abilities to the organization (Beckman et al., 2007; Zarutskie, 2010). The underlying argument is that groups with various skills take better decisions because they have access to more information (Hong and Page, 2001). Therefore, the solutions to new issues encountered during entrepreneurial cycles might result from recombining existing knowledge under new forms. This article argues that start-up teams with diversified skill sets have a better chance of luring investors.

The first reason relates to the decision-making process. In fact, during the early stages, start-up teams must make decisions of various magnitudes in order to develop the firm. Therefore, the success of the digital firm depends on the quality of decisions, and the diversity of skills of a start-up team can improve this process through the synthesis of different resources (Sirmon et al., 2011). Furthermore, a team's functional diversity indicates the presence of more significant cognitive resources at their disposal (Bunderson and Sutcliffe, 2002). For instance, a recent meta-analysis by Jin et al. (2017) shows that entrepreneurial teams with a wide range of skill sets use various market entry, internationalization or innovation strategies (Boeker, 1989). Therefore, a start-up team can make better decisions by utilizing the synergy skills' diversity. Thus, investors may use start-up teams' skills diversity as a signal to assess the performance of a start-up team, which in turn affects the odds of receiving fundings.

The second reason related to the connection between start-up teams'skills diversity and their social capital. The analysis of social capital mechanisms in an entrepreneurial context is well documented in the literature. One way investors use the social capital of start-up teams is as a potential control for asymmetry of information (Ko and McKelvie, 2018). For instance, Shane and Cable (2002) demonstrate how social capital plays a role in the interpersonal relationships between the start-up teams and investors, even going so far as to facilitate fundraising thanks to access to high-level partners. Various prior affiliations can lead to new contacts and insights (Beckman et al., 2007). According to empirical studies, a social connection to a potential investor can increase confidence and provide a channel for the two parties while reducing the informational gap that might otherwise exist between them (Huang and Knight, 2017; Shane and Cable, 2002; Shane and Stuart, 2002). In addition to the direct connections between start-up team members and external investors, researchers suggest that the social capital of a start-up team serves as a signal, influencing investors' perceptions of the underlying quality of the company (Hoenig and Henkel, 2015; Shane and Stuart, 2002). The researchers' mechanism demonstrates that investors use a combination of indicators to triangulate a firm's quality and that the composition of a start-up team and their relationships act as indicators of this quality (Plummer et al., 2016; Semrau and Werner, 2014)

So, if a start-up team's diversity of skills is the result of different social capital and this capital influences the start-up teams' ability to raise funds from investors, start-up teams with diverse skill will raise more funds than less diversed ones.

H2: Start-up teams with greater skill diversity will get more fundings from investors

3 Methodology

3.1 Data sources and collection process

To test our hypotheses, we built a dataset with information on digital firms, their fundraising activities, and granular information on the competencies of start-up teams. Table **??** lists our empirical variables, definitions, and sources. Table **??** provides the general statistics and distribution across sizes and sectors. Table **??** provides the descriptive statistics of the fundraising activities of the 498 digital firms in our sample. We detail the collection process below.

INSERT TABLE 1 HERE

First, we draw on Crunchbase, Dealroom, and BPI France databases as a starting point. These databases provide information on the firm's headquarters, founders' names, fundraising activity, business models, and date foundation. We collected this data in March 2020 and kept firms that (i) were founded between 2010 and 2018, (ii) had their headquarters in the Metropolis of Greater Paris (France), (iii) were independent (no subsidiaries), (iv) operate in business to business markets and (v) used digital Software-as-a-Service (SaaS) business models. From these filters, we ended up with 498 SaaS digital firms[1]. These criteria were chosen as a way to pinpoint the mechanisms that matter most to start-up teams working a given context. In fact, the dynamics of composition for start-up teams

[1] Regarding the filters (iv) and (v), we manually checked each firm's websites to check if their offers included hardware devices and if they depended on a parent company. These filters eliminated x firms (x firms with hardware business propositions and x subsidiaries)

based in other regions may differ significantly; sampling start-up teams from a broad landscape could introduce noise into a focused investigation. Therefore, we could create accurate theoretical models for one particular area (Metropolis of Greater Paris) and domain (the digital) through focused research, in order to produce practical guidance for start-up teams' leaders and members in that location[2].

INSERT TABLES 2 AND 3 HERE

Secondly, we use LinkedIn, a social networking service providing information on individuals' professional trajectories, to collect human capital - skills data of entrepreneurial teams of 498 digital firms, representing a total of x individuals. Virtual skill endorsement (skills endorsed and validated by peers on LinkedIn) is a socially constructed online reputation considered a piece of valuable information. Skill endorsement a way of self-presentation through which the job seekers brand themselves to the potential recruiters (Rapanta and Cantoni, 2017). Using Linkedin has proven its relevance in recent entrepreneurship studies because it profiles detailed individual-level human capital data not available through more traditional sources.

[2]We chose to study SaaS-based digital firms because their scalability echoes the efficient, predictable, and repeatable systems that provide investors with new opportunities offered by the non-linear revenues of digital technologies (the hardware being complicated to finance by investors) (Nambisan, 2017). Also, we chose the period 2010-2018 because it fits with private firms' mass adoption of cloud technologies in pre-existing markets. Indeed, these technologies recently revolutionized the software industry in various markets, e.g., supply chain, financial, accounting, human resources, or customer relationships, making it a topic of interest in various industries (Luoma et al., 2018). Furthermore, we chose the Metropolis of Greater Paris (France) because it is a significant global city with labor and financial capital pools and proximate clients. The Metropolis of Greater Paris' financing and business landscape, especially its venture capital market, is one of Europe's largest, most structured, and most dynamic. From 2016 to 2020, SaaS-based firms accounted for 50% of the total amount raised in France, 75% of French fundraising rounds in Paris, and more than 85% of the amount and in values (BPI, 2020)

We selected carefully all founders that possess equity in the firm (Knight et al., 2020; Xie et al., 2020). Table **??** list the descriptives statistics of all variables (means, std dev, min, max).

INSERT TABLE 4 HERE

3.2 Dependent variable: fundraising

La performance des firmes digitales a été opérationnalisée de nombreuses façons parce qu'il n'y a pas de consensus dans la littérature sur la façon de mesurer leur performance. Par exemple, les chercheurs ont opérationnalisé la performance en termes de croissance (des ventes, d'emplois, de revenus), de rentabilité, de survie, d'innovation ou d'introduction en bourse (IPO) (Delmar et al., 2003).

L'obtention d'un financement externe par un investisseur est la façon dont nous évaluons la performance des firmes digitales. Nous avons choisi la métrique *fundraising* car des recherches antérieures indiquent que recevoir un financement d'un investisseur est un prédicteur important de la survie et de la croissance future d'une firme (Beckman et al., 2007). Notamment, l'insuffisance des ressources financières est fréquemment citée comme la principale cause de l'échec des nouvelles entreprises au début de leur cycle de vie (Franke et al., 2008; Eddleston et al., 2016). Nous avons donc deux populations bien distinctes dans notre échantillon : les firmes ayant reçu un financement de la part d'investisseurs externes, et celles n'en ayant pas reçu.

Nous avons ajouté à cette dummy variable le montant des fonds reçus par les start-up de la part d'investisseurs externes lors du premier tour de financement, qui est lié à leurs évaluations des performances futures de la start-up. Conformément aux études précédentes, nous utilisons le logarithme du premier tour de financement (*log fundraising*). Cette variable s'étend de x à une valeur maximale de x.

Enfin, nous avons ajouté la variable (*time to fundraising*) car du point de vue d'une start-up team, il est souhaitable d'obtenir un financement externe, idéalement peu de temps après la création de l'entreprise, afin d'embaucher plus de personnel et de faire croître l'entreprise. Nous utilisons Crunchbase pour identifier la date de création de l'entreprise et la date à laquelle le premier financement externe a été annoncé. Cette variable s'étend de x à une valeur maximale de x.

3.3 Independant variables

Le niveau de compétences est mesuré au travers d'une variable continue que nous nommons *level skills*, allant de x à x (x = faible niveau de compétences ; x = niveau maximum de compétences). Tous les individus sont placés sur ce continuum dans chacun des cluster de compétence que nous avons récupéré de Linkedin. Nous attribuons à chaque start-ups teams de notre échantillon le score le plus élevé associé à l'un de ses fondateurs. Nous avons construit cette variable comme une variable continue car nous soutenons qu'un clustering dur (catégories) ne rendrait pas compte de la versatilité de l'effet proportionnel qu'il pourrait avoir sur la collecte de fonds (fuzzy clustering). Par conséquent, un score élevé correspond à un avantage supplémentaire pour les start-ups teams.

La variété des compétences est mesuré au travers d'une variable continue que nous nommons *variety skills*, allant de x à x (x = faible variété de compétences ; x = maximum variété compétences). Une start-ups team est considérée comme plus variée sur le plan fonctionnel si les individus sont également répartis dans toutes les différentes catégories fonctionnelles (Blau, 1977 / Hirshman), qui sont des groupes ayant des backgrounds communs. Following Harrison and Klein (2007), we interpret a *variety skills* as *the composition of differences in skills among agents of a unit member*, being here the start-up team. Based on Linkedin individuals' skills and competencies data (from 1,100 unique agents, we gather 10,638 skills, including 5,449 unique skills). We assigned each founders in the dataset a score in ten functional areas (strategy, marketing, entrepreneurship, sales, software development, product, finance, management, human resources, and design). We used a bottom-up hierarchical clustering approach with Kruskal's minimum spanning tree algorithm (Kruskal, 1956) and considered the occurrences and co-occurrences of skills between founders. Therefore, the similarity between any pair of skills is naturally defined as the "intersection over union". Consequently, we set a founders' affinity to any skill cluster in the tree by measuring the skills they share. Instead of assigning a founder to the cluster with the highest affinity (hard clustering) that would not account for its versatility, we describe a founder with his set of affinities to the skills of interest (fuzzy clustering). Finally, we aggregated the founders's variety scores at the start-up team level. We can follow Mintzberg et Waters (1982), Pavett et Lou (1983) et Shein (1987) : il existe 3 rôles dans les entreprises : entrepreneurial (sales SaaS, Biz strat, designer, creation), manager (HR, finance, lawyer) et techniques (utilisation d'outils, procédures, techniques).

3.4 Control variables

We have ve included several control variables because the influence of other factors could skew our estimation.

First, we used the variable *size* to control for start-up team's numerosity. Indeed a higher skill level and a greater variety of skills and conflicts among the members of an organization are implied by a larger population of individuals (Eisenhardt and Schoonhoven, 1990). Our sample has groups ranging in size from x to x.

Secondly, we used the variable *previous founder* whose minimum and maximum values are x and x, respectively, to control the number of firms previously founded by the individuals in our sample. Indeed, a more extensive entrepreneurial experience can increase investor confidence, send a signal of competence, and have an impact on the amount of raised funds. Prior successful foundational experience — mainly financial — increases the likelihood of financing and firm valuation (Hsu, 2007).

Thirdly, using the variable *previous fundraising*, we controlled whether members of the start-up team had previously raised money from investors. Though the investors believe it, it is exceedingly difficult to determine whether serial entrepreneurs are better or worse than the other founders. Even serial entrepreneurs who have failed receive much better terms from investors even though their businesses perform less well when they receive funding (Nahata, 2019).

With the variable *previous exit*, we partially controlled whether members of the start-up team had previously completed a successful exit. Indeed, Gompers et al. (2010) suggests founders who start successful firms have much higher success rates in subsequent firms than founders of unsuccessful firms or first-time founders.

Also, with the *previous career* control variable, we could determine whether the start-up team members had any significant prior professional experience. Indeed, using human capital and signaling theory, Subramanian et al. (2022) investigated whether and how the human capital indicators of founders' educational attainment, professional experience, and personality traits affect early-stage venture capital (VC) investment. They concluded that founders with extensive professional experience attract higher initial investments than other founders.

Sixth, we used the *previous education* variable to determine whether the members of a start-up team attended a prestigious university. Indeed, Ratzinger et al. (2018) demonstrated that founders with degrees from first-plan institutions attracted significant early-stage investments. Additionally, teams founded by Ph.D. holders are more likely to receive funding and higher valuations, suggesting a signal effect. We Therefore have added the *previous Ph.D.* variable (Hsu, 2007).

Finally, we controlled for the birth date and industry in which the firm operates because there may be some confusion due to the financial circumstances in which digital firms operate. We have created six sectoral economic indicators (RH, BI), and one for each year between 2010 and 2018.

3.5 Econometric Specification

Dans cette étude, nous utilisons un Modèle linéaire généralisé utilisant une distribution binomiale négative. La régression binomiale négative sert à modéliser les variables de comptage, généralement pour les variables de résultat de comptage surdispersées (ici, le montant levé par la firme digitale) https://stats.oarc.ucla.edu/r/dae/negative-binomial-regression/

4 Results

4.1 Findings

4.2 Robustness tests

5 Discussion

This article investigates how start-up teams' compositions affect investors' assessments. By highlighting the significance of start-up teams' skill level and skill diversity in obtaining private funding, we try to understand why the results of previous studies on start-up teams' human capital could have been more consistent. Indeed, empiric results from entrepreneurship research have highlighted the founders' human capital as the primary driver of their ability to expand. However, these studies needed did not demonstrate how the skill level and skill diversity within a start-up team can influence a digital firm's success. By examining these two metrics together, this article attempts to center the investigation on the dynamics of early-stage start-up teams and determine how vital these characteristics are to the dynamics of interactions among team members and how they relate to the structure's proper operation. Given the significance of digital firms as a catalyst for economic development, these perspectives are significant for researchers, entrepreneurs, and policymakers.

The lack of research on multiple levels regarding human capital is the primary motivation behind this study. One issue is that the results of (Marvel et al., 2016) show a strong bias toward the individual level, with little consideration given to the founding team or potential inter-individual synergies. Another reason is that the study context varies depending on the sample sizes and populations being looked at. For example, some analyze high-tech and textile industries, while others use samples of student entrepreneurs. After that, it becomes difficult to analyze this relationship without considering the specific circumstances and conditions that apply to a given event or situation, making the study's context — in this case, the digital environment — an essential factor. The insufficient precision of the independent variables used and constructed to represent the variables of human and social capital is a third reason (Harrison and Klein, 2007). In addition to the challenge of incorporating multiple signals and their interactions into empirical studies, previous empirical studies frequently used raw measures of human capital, such as the level of years of education, entrepreneurial experiences, or professional experiences. Therefore, there is a clear need for more precise approaches that reflect a finer variation of human and social capital-related aspects. This article focuses on the latter limit, i.e., we examined the combined effects of two variables and made suggestions regarding how they affect the ability of start-up teams to raise capital from investors. For this, we used a sample of 498 digital businesses with Paris headquarters that use the Software-as-a-Service (SaaS) business model, of which x raised money while x did not do so between 2010 and 2020.

Our findings demonstrate that, in line with the signal and human capital theory, a start-up team that is diverse in terms of skills is more likely to be financed by investors. Another significant moderator of the investment decision is the team size. On the other hand, consistent with our arguments, we discovered that investors favor start-up teams that have (i) either a high level of skills, (ii) either a high level of variety of skills, but not both at once. Because of this, start-up teams that contain highly skilled individuals in related fields, i.e., e. the diversity of their expertise is low, receive more financial resources. High levels of skills, however, hurt the amount and speed of funding start-up teams can secure from investors when their skills are diverse.

The article makes several contributions. First, our findings offer fresh avenues for reflection on the composition of start-up teams and the signal generated among investors. Indeed, past empirical studies have long focused on one of the two dimensions of start-up teams' skills. On the one hand, they either focus on their proficiency level, referring to the novice vs. expert, operationally measured by years of experience. On the other hand, they focus on the level of skills' variety, referring to the specialist vs. generalist and operationally measured by the Hirschman or Blau Index). However, when separated, a firm's success is not explained by either of these two dimensions. Furthermore, not only do some levels of skills only apply to some contexts, but certain levels of variety of skills only apply to some contexts. Indeed, the digital context, in contrast to the industrial context, is governed by other social and technological specificities that require different signals. We suggest a methodology in which we assess these two aspects jointly in a digital context. Second, many empirical studies looking at how start-up teams'composition affects investors' evaluations focused on indicators such as education (Franke et al., 2008), entrepreneurial experience (Beckman et al., 2007), industry experience (Becker-Blease and Sohl, 2015), or leadership experience(Hoenig and Henkel, 2015). In this article, we suggest a skill-based approach, i. e. we focus on "outcomes of human capital" (i. e., their knowledge, skills, and abilities) because they are thought to be more accurate and direct indicators than "investment in human capital" measures like education and years of experience (Unger et al., 2011; Marvel et al., 2016). Third, this is a chance to focus on the most crucial systems for teams in that area. As previously mentioned, selecting teams from a wide swath of the landscape could introduce noise into a targeted investigation because the dynamics of composition for teams located in other regions may be quite different. By focusing our research on a small landscape area, we can create accurate theoretical models for that area and create helpful suggestions for team leaders and members of start-ups operating in that area

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