Online skills endorsement and start-up funding: evidence from new digital ventures in the greater Paris

Abstract

Securing financial capital from external stakeholders is crucial for the survival and expansion of start-up teams. However, accurately predicting the eventual success of these start-up teams presents a considerable challenge for investors. Drawing on insights from signaling theory and human capital literature, our research highlights the role of online skills endorsements of start-up teams — a peer-reviewed measure of human capital available on professional social networks — and its potential signaling effect and consequent impact on a start-up team's ability to attract early-stage venture funding. Analyzing a dataset of 439 French start-up teams, we found that teams comprised of highly skilled individuals from diverse fields may not fully exploit the benefits of their varied skills, knowledge, and social capital. Our study unveils that investors typically favor teams with either a high level of endorsed skills or a wide variety of endorsed skills, but seldom both simultaneously. Hence, our study enriches the academic literature surrounding the use of online skill endorsements as complementary human capital measures with potential signaling impacts on early-stage resource acquisition. In practical terms, our findings offer valuable insights for entrepreneurs utilizing professional social networks for their fundraising activities.

Keywords: online endorsement, fundraising, start-up teams, variety, human capital, signaling theory

JEL Classification: L22, L26, L85

1 Introduction

Which start-up teams are funded and why are recurring themes in contemporary economic and entrepreneurial literature (Baum and Silverman, 2004; Beckman et al., 2007; Bernstein et al., 2017; Franke et al., 2006, 2008; Kaplan et al., 2009; Plummer et al., 2016; Shane and Cable, 2002). In entrepreneurship literature, start-up teams, defined as groups of individuals exhibiting attributes such as equity ownership, decision-making autonomy, and entitativeness (Knight et al., 2020), are recognized as essential agents for the development of cities, regions, and countries due to their role in firm creation and growth (Audretsch and Thurik, 2001; Autio, 2016). Acquiring financial resources is a key factor for their survival and expansion (Rosenbusch et al., 2013), thus making the determinants of attracting such resources of great interest to researchers, practitioners, and policy makers (European-Commission, 2015).

The literature underlines the complex relationship between start-up team composition on investor decisions (Ghassemi et al., 2015; Klotz et al., 2014). Start-up teams qualities such as founders' education, prior work experiences or competences (Errico et al., 2023; Shane and Cable, 2002; Hsu, 2007), and their relationships with investors and partners (Huang and Knight, 2017), serve as quality signals for obtaining financial resources. While these studies yielded important insights, this approach is problematic as investors nowadays draw on a wide range of other signals to assess the relevance of investing in a start-up team. For instance, Banerji and Reimer (2019) found that founders' number of followers on their LinkedIn profiles was the strongest predictor of the amount of funds raised by new ventures. In the same vein, based on data available on Kickstarter crowdfunding website, Mollick (2014) evidences that founders' Facebook connections help equity crowdfunding success and Courtney et al.

(2017) show how third party online endorsements help firm attract fundings.

Within professional social networks, the endorsement feature is a socially constructed online reputation measure and a method of self-presentation, enabling job seekers to brand themselves to potential recruiters (Rapanta and Cantoni, 2017). For instance, endorsements showcased on a candidate's profile allow potential employers to evaluate the individual's skills with increased confidence, rather than relying solely on a review of their CV (Drakopoulos et al., 2020; Pérez-Rosés et al., 2016; Yan et al., 2019). This feature has been incorporated into several social networks, such as LinkedIn and ResearchGate, allowing users to earn endorsements for specific skills tied to authority and social credit (Pérez-Rosés et al., 2016; Rapanta and Cantoni, 2017; Wu et al., 2018). In LinkedIn, the largest professional online social network in the world (Wu et al., 2018), this feature has been introduced in 2012, and enables LinkedIn users to associate themselves with topics indicative of their expertise and to receive social proof of their competence in these areas from their connections. In entrepreneurship research, scholars have deemed online skill endorsements as valuable data for entrepreneurial studies and perceive them as a reliable criterion to assess a person's knowledge (Gasiorowski and Lee, 2022; Reese et al., 2020; Sako et al., 2020). However, the potential signaling effects of online skill endorsements on early-stage resource acquisition have not been explored by researchers. This gap in the literature is noteworthy, particularly given the heightened levels of uncertainty (Matusik et al., 2008) and information asymmetry between the signal sender and receiver (Harrer and Owen, 2022; Spence, 2002) at this stage. Thus, any quality signals that provide an additional perspective and aid in triangulating start-up team data are greatly appreciated by investors because at this point, a new venture typically lacks a performance track record to lean on, but it must nevertheless convince investors of its legitimacy (Becker-Blease and Sohl, 2015), thereby making it worthy of acquiring essential resources, such as financial capital (Ko and McKelvie, 2018).

This study seeks to fill this gap by examining the role of start-up teams' online skills endorsement in resource acquisition during the early stages. Drawing on the theory of signaling and human capital literatures, we propose that teams made up of highly skilled individuals from diverse fields may not be fully leveraging the benefits of their varied skills, knowledge, and social capital. To test our propositions, we use data from a sample of 439 french digital new ventures and human capital data on their start-up teams. We constructed a unique dataset that includes "human capital investments" (i.e., common traditional signals used by investors such as years of education, professional experience, and previous founding experience) and "outcomes of human capital" (i.e., skills, abilities and knowledge) based on online endorsements data (Marvel et al., 2016; Rapanta and Cantoni, 2017). We use the later as our main independent variable and the former as moderating variables. We analyze our statement in two stages. First, we examine the relationship between the level of online skills endorsement of start-up teams and its impact on capital acquisitions in early-stage investment. Secondly, drawing from the cognitive distance model (Nooteboom et al., 2007) and the cybernetics principles of requisite variety applied to the entrepreneurship literature (Ashby, 1957; Harrison and Klein, 2007; Sundermeier and Mahlert, 2022; Villani et al., 2018), we assess the extent to which signals from start-up teams' online skills endorsements variety help the firm acquire capital. Following our claims, we find that investors favor start-up teams that have either a high level of competency or a high level of variety of skills, but not both at once.

This study aspires to enrich the literature from two distinct perspectives. First, we aim to extend past research is start-up team composition (Beckman et al., 2007; Jung et al., 2017). Despite the pervasive mention of team composition in the corpus of literature pertaining to start-up teams, there seems to be a dearth of agreement on the precise process by which composition influences outcomes, and the circumstances under which these effects might be significant (Klotz et al., 2014; Zhou and Rosini, 2015). Our endeavor is to offer fresh perspectives in the trade-off between homogeneity and heterogeneity regarding skills in start-up teams (Sundermeier and Mahlert, 2022; Villani et al., 2018). Second, by building upon the literature on signaling and new venture financing (Colombo, 2021; Drover et al., 2017; Klein et al., 2020), this paper seek to expand upon previous investigations of the effect of human capital on venture financing (Banerji and Reimer, 2019; Marvel et al., 2016; Mollick, 2014; Reese et al., 2020) by explicitly examining the signaling impact of online skills endorsements on resource acquisition. We aim to demonstrate the utility of online endorsements data for research, specifically to elucidate the dynamics of new venture signals in entrepreneurship literature (Pérez-Rosés et al., 2016; Gasiorowski and Lee, 2022).

The paper is structured as follows. Section 2 reviews the literature on signaling theory for early-stage resource acquisition. Section 3 explains the data and methods used, and Section 4 presents key findings. Finally, section 5 concludes by discussing implications for entrepreneurship and new venture financing literature, noting the limitations of this study.

2 Theoretical framework and hypothesis

2.1 Signaling theory for early-stage resource acquisition

Literature on entrepreneurship has continually underscored the critical role of financial resources for the survival and growth of new venture (Cooper et al., 1994; Drover et al., 2017; Klein et al., 2020). However, securing funding from external investors is a challenging task, with investors having difficulty predicting which teams will come out on top (Ghassemi et al., 2015), notably due to the inherent information asymmetries between them and venture founders, or the lack of past financial results. In order to mitigate the information asymmetries, investors draw on quality-signals (Harrer and Owen, 2022; Ko and McKelvie, 2018; Subramanian et al., 2022), with signalling theory being particularly applicable in the uncertain entrepreneurial processes (Spence, 1978).

Signaling theory posits that two parties take conscious and voluntary steps to reduce asymmetric information and perceived uncertainty between them, and this is done by focusing on the signals available to them (Spence, 1974). This concept has been used in various disciplines to provide insight into social selection problems when there is an absence of perfect information (Connelly et al., 2011; Colombo, 2021). Entrepreneurship scholars have found this concept to be beneficial as particular signals can diminish uncertainty about ventures' quality in the eyes of stakeholders, such as prestigious government grants (Islam et al., 2018), the enthusiasm and passion of the founders (Chen et al., 2009), affiliations of the venture with other entities (Plummer et al., 2016), previous occupational characteristics and experiences (Wu et al., 2023) and the composition of the founders' team (Ko and McKelvie, 2018). Investors, similarly, use a variety of indicators to mitigate asymmetric information such as the founders' ties to others (Shane and Cable, 2002), communication tools (Harrer and Owen, 2022), endorsements (Courtney et al., 2017; Janney and Folta, 2006; Plummer et al., 2016; Gasiorowski and Lee, 2022), social capital (Shane and Stuart, 2002) or human capital (Beckman et al., 2007).

In the context of early-stage ventures, human capital characteristics of the start-up teams is considered to be a significant and prominent factor for investors to consider (Beckman et al., 2007; Ko and McKelvie, 2018; Matusik et al., 2008). This emphasis is due to the limited resources and small number of people responsible for formulating and carrying out strategies. According to the organizational theory perspective applied to the entrepreneurship field, the human capital composition of the start-up teams is believed to have an imprinting effect on the processes and operations of the firm (Packalen, 2007). This concept implies that past experiences, and therefore the underlying skills and experiences acquired meanwhile, can shape the present and future performance (Wu et al., 2023). Concretely, investors aim to reduce uncertainty about the quality of the firm by relying on the human capital and demographic characteristics of start-up teams such as their educational background or their functional skills because these are easily accessible quality-signals (Colombo and Grilli, 2005; Beckman et al., 2007; Eddleston et al., 2016; Plummer et al., 2016). Extensive research has been conducted to explore the association between signaling and the acquisition of financial resources (see Connelly et al. (2011) and Colombo (2021) for a review). However, investors nowadays draw on a wide range of other signals to assess the relevance of investing in a start-up team (Banerji and Reimer, 2019; Mollick, 2014; Courtney et al., 2017), and a remaining challenge is the examination of the signaling role of online skills endorsement available on professional social networks (Drakopoulos et al., 2020; Pérez-Rosés et al., 2016; Rapanta and Cantoni, 2017; Yan et al., 2019) on financial resource acquisition in new venture early stages.

2.2 Skills endorsement as a peer-reviewed measure of human capital

Professional social networks have emerged as primary conduits of data, generating an extensive pool of information that, when harvested, analyzed, and refined, becomes a valuable resource used by organizations (Ponte et al., 2022). According to (Urdaneta-Ponte et al., 2021), many companies have started incorporating this new source of data into their recruitment processes, with LinkedIn (which boasts over 650M+ users) being the top choice. On this platform, members reveal career-specific information, including occupation details, education, and skills. For (Rapanta and Cantoni, 2017), LinkedIn is one of the most influential web resource and social network for professional use, as it allows members to endorse each other's skills. This unique feature of LinkedIn has led to a surge in research around the concept of endorsements.

For instance, the study conducted by (Yan et al., 2019) uses endorsements as a tool to assess the depth of skills, thereby deducing the professional expertise of LinkedIn members. Similarly, (Drakopoulos et al., 2020) use endorsements to determine a user's skills, providing a measure of credibility for potential start-up candidates. The innovative approach suggested by (Constantinov et al., 2015) extracts skill sets from LinkedIn and evaluates their competency level based on endorsements, thereby identifying a range of competencies demanded by the market. These competencies then form the foundation for curriculum construction. A similar perspective is also used by Wu et al. (2018) who suggest that firms use this information in their recruitment strategies to select the most suitable candidates for their vacancies.

In all the research mentioned above, skill endorsement is viewed as a peer-reviewed measure of human capital. The endorsement feature empowers members to associate themselves with domains that reflect their expertise, while their network validates these claims by endorsing the member's proficiency in the chosen domain (Pérez-Rosés et al., 2016). As a result, potential investors might assess the endorsed skills exhibited on the applicant's profile to evaluate the quality of the firm and the human capital attributes of start-up teams, rather than simply reviewing their CV, which displays more conventional human capital indicators, such as prior professional experiences and academic qualifications (Gasiorowski and Lee, 2022). In the following section, we leverage this body of work to examine the signaling effect stemming from the proficiency level and diversity of skill endorsements within start-up teams.

2.3 Signaling effects from start-up teams' level and diversity of skills endorsement

Entrepreneurship researchers have extensively explored what start-up teams' characteristics enable them to access external funding (Roure and Keeley, 1990). 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). Such characteristics include the team's demographics and size (Eisenhardt and Schoonhoven, 1990), the teams' match with an investor's characteristics (Aggarwal et al., 2015), the industry environment (Townsend and Busenitz, 2015) or the investor's experience (Franke et al., 2008). However, in the context of early-stage ventures, "human capital outcomes" (i.e. agents' "observable applications or know-how related to a domain" (Becker, 1964; Marvel et al., 2016)) of the start-up teams is maybe the most significant and prominent factor for investors to consider (Beckman et al., 2007; Ko and McKelvie, 2018; Matusik et al., 2008).

Conformed to the human capital literature applied to the entrepreneurial field, we postulate that start-up teams with higher levels of skills endorsement have a greater propensity to reach specific entrepreneurial milestones, elicit greater investor confidence, and a greater likelihood of attracting external financial capital. There are several reasons for such a claim. First, it has been shown that higher levels of skills enable founders to take greater risks and demonstrate proactive behavior (Becherer and Maurer, 1999), allowing them to optimize business opportunities (Shane and Venkataraman, 2000; Chandler and Hanks, 1994). Additionally, the acquired skills enable entrepreneurs to make full use of the available technological tools (Nambisan, 2017), enabling them to better understand and differentiate their offerings through the introduction of new technologies and disruptive products (Marvel and Lumpkin, 2007). Moreover, a high level of skill proficiency can help entrepreneurs to obtain resources complementary to financial resources, which is an issue for many firms in the early stages of development (Beckman et al., 2007). Finally, developing skills and knowledge is a prerequisite for further entrepreneurial learning and helps acquire additional skills and knowledge that will help firm to grow (Hunter, 1986).

Therefore, we propose that a high level of skills endorsements 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 alterted by this signal because it suggests that higher skill levels may translate into future success. Thus, we hypothesize the following:

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

In this study, we consider not only the level of skills endorsement but also their diversity at the team level (Harrison and Klein, 2007; Sundermeier and Mahlert, 2022). Diversity is a concept in line with the information / decision-making perspective, which posits that diversity of task-relevant resources increases the potential for developing synergistic solutions that are superior to those attainable by homogeneous groups with a more limited pool of resources (Williamsky, 1998). In our perspective, online skills' diversity in a start-up team matters because the success of entrepreneurial initiatives is often the result of teamwork and collective endeavors, which require the combination of knowledge, the synergy of abilities, and the collaboration of multiple individuals (Klotz et al., 2014). Therefore, we argue that start-up teams with a wide range of skills endorsement have a greater chance of acquiring investors due to two key reasons.

The first reason relates to the decision-making process. 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. A meta-analysis conducted by Jin et al. (2017) suggests that an entrepreneurial teams endowed with a varied skill set are more likely to use various market entry, internationalization or innovation strategies. This implies that start-up teams with diverse skills are in a better position to make high-quality decisions, thus increasing their chances of success. Consequently, investors may use start-up teams' skills diversity as a signal to assess their future performance, which can significantly impact the probability of receiving investments.

The second reason related to the connection between start-up teams' skills diversity and their social capital. Evidence shows that the social capital of a start-up team has the capacity to act as control for information asymmetries. Indeed, Huang and Knight (2017) and Shane and Stuart (2002) posit that the presence of a social connection between start-up teams and investors can reduce the informational gap between them. In the same vein, Shane and Cable (2002) infer that social capital play a role in connecting start-up teams to potential investors and facilitating fundraising. Additionally, Hoenig and Henkel (2015) suggest that the social capital of a start-up team is utilized by investors to triangulate the quality of the firm and the composition of start-up teams and their relationships (alliances) are used as indicators of quality by investors (Plummer et al., 2016; Semrau and Werner, 2014). Following these rationales, if a start-up team's diversity of skills endorsements is the result of different social capital and given that capital influences the start-up teams' ability to raise funds from investors, start-up teams with diverse skills might therefore raise more funds than less diversed ones. Thus, we hypothesize the following:

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

The past rationale invite us to think that having high both highly skilled individuals and a high levels of diversity is beneficial for firm performance (Díaz-Fernández et al., 2020). However past findings suggest that adding more human capital to a start-up team does not necessarily translate into greater success (Pierce and Aguinis, 2013; Sundermeier and Mahlert, 2022). This calls into question the positive relationship between diversity and performance, as diversity can introduce additional costs related to communication and coordination. Indeed, if empirical entrepreneurship studies evidence that a particular level of expertise stimulates the detection of new business (Shane and Venkataraman, 2000; Marvel et al., 2016), elevates the likelihood of generating remarkably new and commercially viable services, and boosts the chances of obtaining external funding (Beckman et al., 2007; Marvel and Lumpkin, 2007), conversely, cognitive and social psychology findings indicate that highly skilled individuals across various fields tend to possess greater cognitive inelasticity and greater cognitive distance (Nooteboom et al., 2007). Cognitive inelasticity arises from the prolonged exposure to a specific field, which engenders a cognitive model that adheres to the prevalent logical pattern of that field. Although cognitive inelasticity can lead to greater determination, it can also diminish one's receptiveness to entirely distinct logics and approaches, hinder communication within a start-up team, and limit the team's exploitation of its knowledge. Therefore, the dangers of cognitive inelasticity are more probable and particularly menacing when two or more persons share a high cognitive distance. Cognitive distance denotes the degree to which two or more people have created distinct cognitive models or belief systems (Nooteboom et al., 2007). Therefore, high cognitive distance may create obstacles to communication and collaboration within a start-up team and limit openness to innovative business models, such as pivoting (Kirtley and O'Mahony, 2020).

Consequently, though any two individuals in a team inherently have some degree of cognitive divergence, those who share comparable abilities and fields of expertise tend to have lower cognitive distance, as they are more likely to be familiar with each other's cognitive models and therefore can establish the essential mutual trust for a social group's effective functioning. Conversely, those with completely different areas of expertise are more prone to possess divergent outlooks and knowledge, thereby increasing their cognitive distance. As a result, this may reduce the quality of their interactions, decisions, and ability to interact effectively. Since the adverse impacts of cognitive distance are more pronounced when group members have firmly established cognitive models and entrenched opinions and positions (i.e., when they are cognitively inflexible), start-up teams comprised of highly skilled individuals from different domains may not fully exploit the benefits of their varied skill sets, information, and social capital. Consequently, we put forth the following hypothesis:

H3: Start-up teams' skill endorsement diversity impact negatively the positive effect of level of skill endorsement on the funds raised

Our formal hypotheses (H1, H2, H3) conform with the proposed model presented in Figure 1

INSERT FIGURE 1 HERE.

3 Method

3.1 Sample and data collection

To test our hypotheses, we constructed a dataset incorporating information at both organizational and individual levels of start-up teams. Table 1 lists our empirical variables, definitions, and sources. Table 2 provides the general statistics and distribution across sectors. Table 3 provides the descriptive statistics of the fundraising activities of the 439 digital new ventures in our sample. We detail the collection process below.

INSERT TABLES 1, 2 AND 3 HERE.

First, we draw on Crunchbase, and BPI France databases as a starting point. The first database follow the evolution of global firms benefiting from venture capital financing. The second is a French state database that lists French-based innovative firms. These databases provide information on the firm's headquarters, founders' names, fundraising activity, business models, and date of foundation. We collected this data in March 2020 and kept firms that (i) were founded between 2011 and 2018, (ii) had their headquarters in the Metropolis of Greater Paris (France), (iii) were independent (no subsidiaries), (iv) operated in business-to-business markets and (v) used a scalable business model in the digital industry. From these filters, we ended up with 439 firms. We study firms with digital business models (i.e., software-as-a-service, marketplaces, and platforms) because they echo the efficient, predictable, and repeatable systems that offer investors new opportunities due to the non-linear revenues of digital technologies (Nambisan, 2017). Unlike traditional software licenses that require installers, scalable business models are hosted in the cloud, require little infrastructure, are searchable using a browser, and are delivered over the Internet with or without a subscription-based revenue logic. We also chose the period 2011-2018 because it coincides with the mass adoption of cloud technologies in pre-existing markets. These technologies have revolutionized the software industry in various markets, such as supply chain, financial, accounting, human resources, or customer relationships, making it a topic of interest in various industries. From 2016 to 2020, software-as-a-service, marketplaces, and platforms firms accounted for 55% of the total amount raised in France, 75% of French fundraising rounds in Paris, and more than 85% of the value (BPI, 2020). 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 one even though characterized by tight links between firms and the state and by powerful elite networks (Milosevic, 2018).

Secondly, we use LinkedIn to collect human capital data of all the founders who worked in these 439 digital firms, representing a total of 1341 individuals. LinkedIn provides granular information on individuals' professional trajectories and users have an incentive to keep their profiles current since the website is valuable for professional networking: many employers use it to recruit new employees, either by posting job ads or through direct headhunting (Pérez-Rosés et al., 2016; Rapanta and Cantoni, 2017; Wu et al., 2018). While job experience is an indicator frequently used in entrepreneurship studies as a predictor for firm performance (see e.g., Colombo and

Grilli (2005) or Delmar and Shane (2006)), skill endorsement (i.e. skills endorsed and validated by peers on LinkedIn) is a socially constructed online reputation and is a way of self-presentation through which job seekers brand themselves to potential recruiters (Rapanta and Cantoni, 2017) considered as a piece of valuable information for entrepreneurial studies. Indeed, using skill endorsements data has proven its relevance in recent entrepreneurship studies because it provides detailed individual-level human capital data not available through more traditional sources. For example, Reese et al. (2020) use LinkedIn information about founders, especially their "skills and endorsements" section, to measure founders' human capital and Sako et al. (2020) used LinkedIn "skill endorsement" section too in order to identify the skills of individual start-ups founders. Table 4 list the descriptive statistics of all variables (means, std dev, min, max).

INSERT TABLE 4 HERE.

3.2 Variables

3.2.1 Dependent variables

Empirical evidence indicates that attracting funding from an investor is a significant predictor of a firm's future survival and growth (Beckman et al., 2007), and inadequate financial resources are frequently cited as the leading cause of failure for new ventures at the onset of their lifecycle (Franke et al., 2008; Eddleston et al., 2016). In this empirical work, we explore two relationships. The first dependent variable is the logarithm of the first round of funding (*log fundraising*) for OLS linear regression. Some new digital ventures did not raise any funds during the observed period. As has been done in previous empirical studies, we include these observations as zero. However, instead of censoring the fundraising variables, we add a small constant to preserve information about the new digital firms. Therefore, the *log fundraising* variable ranges from 0,001 to a maximum value of 16,524.

Second, we aim to examine how online skills endorsements correlate with the performance outcomes of VC-backed digital ventures. Accordingly, in line with previous studies, we use Logit as our main regression model, as it has been extensively applied in recent entrepreneurial finance research studies (Ahlers et al., 2015; Islam et al., 2018).

3.2.2 Independant variables

The main independent variables are *Skills level* and *Skills field variety*. Methodologically speaking, to develop these two variables, we underwent two phases of data pre-treatment.

In the first phase, using online skill endorsement data from LinkedIn (Rapanta and Cantoni, 2017), we assigned a score to each team members in the dataset for six functional areas, namely Finance, Product, Development, Management, Marketing, and Entrepreneurship. To create the six functional areas, we make use of the semantic web and employed a bottom-up hierarchical clustering approach with Kruskal's minimum spanning tree algorithm (Kruskal, 1956), taking into account the occurrences and co-occurrences of skills endorsement among individuals because individuals usually have more than one skill, with some of those skills being related (Pérez-Rosés et al., 2016). Therefore, the similarity between any pair of endorsed skills is naturally defined as "intersection over union". Consequently, we determined an individual's affinity to any skill cluster in the tree by measuring the skills that individuals share. In other words, instead of assigning an individual to the cluster with the highest affinity (hard clustering) that would not account for their versatility, we describe an agent by their set of affinities to the skills of interest (fuzzy clustering). This supervised machine learning model is not new and is frequently used in entrepreneurship and management studies to build semantic web ontologies (Kaushal et al., 2021; Ponte et al., 2022). Furthermore, building on such ontologies also help to standardize skills from social networks that are related (Pérez-Rosés et al., 2016). In the second phase, we followed the practices of entrepreneurship studies and standardized the scores of each individual to make them comparable across an ordinal variable (Harrison and Klein, 2007). Specifically, we assigned a ranking to the 1341 individuals from the 439 start-up teams for each functional area based on 10 quantiles, where the 0th quantile represented the lowest level and the 9th quantile represented the highest level of skill endorsement. We developed this variable as an ordinal one, as we contend that for each degree of online endorsement achieved, there is a commensurate effect on the ability to obtain financial resources. Thus, each level corresponds to an incremental advantage for start-ups seeking to secure funding.

From the pre-treatment data process used to generate individual scores, we now possess the necessary raw material to compute firm-level scores for *Skills level* and *Skills field variety*. To measure the start-up team's *Skills level* score, we assigned the highest median score in the six functional areas associated with any of its founders. To measure the start-up team's *Skills field variety* score, we assigned a variable that captures the number of different fields of expertise of its founders. Following Harrison and Klein (2007), we interpret diversity as *variety* defined as *the composition of differences in skills among agents of a unit member*, in this case being the start-up team. Concretely, we compute the variable score based on Blau's index, where the variable is equal to $1-\sum p_k^2$ where p is the proportion of unit members in kth category, ranging from zero to $k - 1/k$.

3.2.3 Control variables

Traditional controls are used to measure entrepreneurs' human capital quality-signals effects.

First, the variable *Previous Prestigious University* was included to take into account the institutionalized cultural capital of the start-up teams members, as defined by Bourdieu (1979). The presence of such capital allows to transmit a quality signal to investors and is thus considered an important factor for start-up teams success. For example, Ferrary (1999) empirically demonstrated that degrees from first-plan institutions contribute to quality-signals. In more details, the this variable is constructed from a combination of the top 10 universities worldwide (ARWU 2022 ranking) and the best French business and engineering schools (Figaro Etudiant Ranking 2023). ARWU is not suitable for capturing the entrepreneurial elite graduated in France, due to the weight and attractiveness of French "Grandes Ecoles", poorly represented in ARWU-type international rankings based on Clarivate bibliometric data. The student Figaro ranking integrates the quality of faculty recruitment, relations with industry, and the salary of graduate students.

Second, we use *Previous Founding Experience* to control the number of firms previously founded by the individuals, also known as serial entrepreneurship (Kirschenhofer and Lechner, 2012). Indeed, a more extensive entrepreneurial experience can increase investor confidence, send a signal of competence, have an impact on the amount of raised funds (Hsu, 2007) and have a positive impact on growth aspirations of subsequent start-ups. (Fuentelsaz et al., 2023).

Third, we control for *Previous Working Experience* to determine whether a start-up team member had any significant prior professional experience. Indeed, using human capital and signaling theory, Subramanian et al. (2022) investigated whether and how founders' human capital characteristics affect early-stage venture capital investment. They concluded that founders with extensive professional working experience attract higher initial investments than other founders.

Fourth, we control for *Previous Ph.D Degree* as teams founded by Ph.D. holders are more likely to receive funding and higher valuations, suggesting a signal effect (Hsu, 2007).

Fifth, we use *New Venture Age* to control for the time in years since the founding date of a new venture to incorporate a for new ventures' stage of development.

Sixth, we controlled for the *Team size* as a larger start-up team may naturally have more skill endorsements simply due to the greater number of individuals. Therefore, controlling for team size can help isolate the specific effect of skill endorsements on early-stage venture funding. Furthermore, investors often consider team size as one of the factors in their investment decisions. Larger teams may be perceived as more capable in terms of delivering on their proposed business plans (Harrison and Klein, 2007; Williamsky, 1998).

Lastly, as there can be confounding effects related to industry conditions in which start-ups operate, we controlled for the *Industry*. In more details, 11 industry dummies were included which take value 1 if the firm is operating in i) Business Intelligence Analytics, ii) Customer Relationship Management, iii) Developers Software Infrastructure, iv) Education Human Resources, v) Finance Legal Insurance, vi) Healthcare, vii) Logistics Supply Chain, viii) Marketing and Media ix) Productivity Collaboration, x) Real Estate Construction xi) Retail Ecommerce.

3.2.4 Models

To test the predictions of our model, we first ran an OLS linear regression with the logarithm of the first round of funding (*log fundraising*) as dependent variable. Correlations among the variables are reported in Table 5. The statistical analyses were conducted with Statsmodels Release 0.13.0. The package is released under the open source Modified BSD (3-clause) license (Seabold and Perktold, 2010). Secondly, we use Logit as our main regression model. The dependent variable is a dummy variable that takes the value of 1 if the firm has raised a seed, 0 if not.

INSERT TABLE 5 HERE.

4 Results

As a first step, we ran an OLS model whose results are reported in Table 6. Model 1 includes only control variables; Model 2 contains only the first independent variable; Model 3 contains only the second independent variable; Model 4 contains the two independent variables; Model 5 comprises the full model with all the independent and moderating variables. We have also controlled for potential multicollinearity problems through a VIF test (James et al., 2013), and no issues of that nature are present.

INSERT TABLE 6 HERE.

In our first hypothesis, we propose that start-up teams with greater skills endorsement levels will get more fundings from investors. Based on the econometric outcomes presented in table 6, the *Skills level* variable in relation to the natural logarithm of funds demonstrates a positive and highly noteworthy value in Model 2 ($p < 0.01$), Model 4 ($p < 0.01$), and Model 5 ($p < 0.01$). Hence, we validate Hypothesis 1.

Subsequently, in our second assumption, we posited that *Skills field variety* among start-up team members would inspire more optimistic investor expectations concerning the future success of a start-up due to a range of mindsets, superior problem-solving abilities, greater social networks, and a higher probability that diverse organizational tasks would be competently executed. Thus, in our second hypothesis, we posited that diversity of skills fields among start-up team members would result in an increased capacity to obtain funding. As the *Skills field variety* coefficient is positive in model 3 and 4 but very significant only in Model 5 ($p < 0.01$), we find only partial support for Hypothesis 2.

Lastly, we developed a negative moderating effect of *Skills level* on the relationship between *Skills field variety* and funds raised by the start-up team. In order to arrive at this reasoning, we put forth the notion that team members in a start-up with advanced levels of skill are subject to cognitive inflexibility. Therefore individuals may struggle to interact effectively with other team members whose mental models differ from their own. Therefore, we conjectured that team members with advanced proficiency may have lower chances of providing constructive inputs to the start-up if their peers possess varied skill sets. Thus, we postulated that investors might show a diminished inclination to invest in start-ups where the members possess both extensive proficiency and a wide range of skill and expertise fields. The interaction term between *Skills level* and *Skills field variety* has negative and significant coefficients ($p < 0.01$) in Model 5, the comprehensive model, thereby providing support for Hypothesis 3.

As a second step, we estimated a logistic regression as a second regression model in which the dependent variable is a binary (*Fundraising*), since it has been widely used in recent entrepreneurial finance research studies (Ahlers et al., 2015; Islam et al., 2018). Again, Model 1 includes only control variables; Model 2 contains only the first independent variable; Model 3 contains only the second independent variable; Model 4 contains the two independent variables; Model 5 comprises the full model with all the independent and moderating variables. Results are reported in Table 7.

INSERT TABLE 7 HERE.

The econometric analysis of the logit regression reveals that the *Skills level* variable exhibits a positive and statistically significant value in Model 2 ($p < 0.05$), Model 4 ($p < 0.05$), and most notably in Model 5 ($p < 0.001$). These findings lend credence to Hypothesis 1.

As per Hypothesis 2, we proposed that *Skills field variety* would catalyze the fundraising process. While the *Skills field variety* coefficient displays a positive orientation in Model 4, it only achieves significance in Model 5 ($p < 0.05$), implying a partial endorsement of Hypothesis 2.

Lastly, we surmised a counteractive role of the *Skills level* in the association between *Skills field variety* and successful capital acquisition. Our assumption finds support in Model 5, where the interaction term between *Skills level*and *Skills field variety* reveals a negative and significant coefficient ($p < 0.05$), thus supporting Hypothesis 3.

5 Robustness tests

We performed several robustness tests to ensure the quality of the analysis.

Corrected Blau index: as varying group sizes in a sample affect the most common measures of group diversity (Biemann and Kearney, 2010), we use an alternative formula to get an unbiased estimation of within-group variety ($1 - \sum(N_i * (N_i - 1))/(N * (N - 1))$, where N_i is the absolute frequency of group members in the ith category and N is the total number of group members). Results remain consistent.

Huber-White test: we utilized this test for heteroscedasticity using the het_white function of Statsmodels Release 0.13.0. (Seabold and Perktold, 2010). In our case, the p-value for the White test is 0.36. Consequently, we cannot reject the null hypothesis that the errors are homoscedastic. This infers that based on the test's results, there is insufficient evidence of heteroscedasticity in our data.

Kruskal's minimum spanning tree algorithm: there might be room for further discourse about the classification of skills into functional domains, specifically about the relevance of bottom-up hierarchical clustering with Kruskal's algorithm (Kruskal, 1956). Certainly, certain skills, like entrepreneurship, might be more or less pivotal for different start-up teams. We executed the regressions and assessments using different skills classifications, and the primary findings remain consistent.

Skills level scores: finally, we also allocated the highest maximum and mean scores of skills level in the six associated functional areas to any of its founding members to the start-up team. The outcomes derived from utilizing alternate estimators align reasonably well with those shown here and can be provided by the authors upon request.

6 Discussion and conclusion

Research has highlighted the complexity of the effects of start-up team composition on investors' evaluations (Cooper et al., 1994; Ghassemi et al., 2015). Prior studies found that individual qualities of founding members, such as their education, work experience, and prior entrepreneurial endeavors (Shane and Cable, 2002; Hsu, 2007), as well as their social capital - the direct or indirect relationships that founding members have with investors, corporate partners, and other entities (Shane and Cable, 2002; Hsu, 2007; Huang and Knight, 2017) - act as signals of venture quality and are therefore determinants of financial resource acquisition. However, this approach is problematic as investors now use a variety of other signals to assess the relevance of investing in a start-up team (Banerji and Reimer, 2019; Mollick, 2014; Courtney et al., 2017). Recent entrepreneurship research has identified online skills endorsement data (Gasiorowski and Lee, 2022; Pérez-Rosés et al., 2016; Wu et al., 2018) as valuable information for entrepreneurial studies and a reliable criterion for judging an individual's knowledge (Rapanta and Cantoni, 2017; Reese et al., 2020; Sako et al., 2020). However, the potential signaling effects of online skills endorsement data on early-stage resource acquisition have been overlooked in the literature as previous empirical studies did not engage efforts into assessing how online skills endorsement can influence a new venture's success in a digital context.

This study address this gap by examining its role in resource acquisition during the early stages of entrepreneurship. Drawing on the theory of signaling and human capital literatures, we explore how this socially constructed peer-reviewed measure of professional capabilities can influence the ability of start-up teams to acquire financial resources from investors. More precisely, in this article we develop and examine two human capital measures simultaneously (skills levels and skills field variety) and focus on the dynamics of early-stage start-up teams and how these characteristics relate to the proper operation of the structure. Using a sample of 439 digital new ventures in the greater Paris, we demonstrate that, investors favor start-up teams that have (i) either a high level of skills endorsement, (ii) either a high level of variety of skills endorsement, (iii) but not both at once. Because of this, start-up teams that contain highly skilled individuals in related fields, i.e., the variety of their skills is low, receive more financial resources.

This research seeks to enrich existing works from two unique angles. First, we built upon prior extend investigations into the composition of start-up teams (Beckman et al., 2007; Jung et al., 2017). Despite the prevalent discussion of team composition within the swathes of literature related to start-up teams, there appears to be a noticeable absence of consensus on the exact modalities by which team composition impacts outcomes, and the conditions that render these impacts meaningful (Klotz et al., 2014; Zhou and Rosini, 2015). Therefore, we introduced new insights into the delicate balance between homogeneity and diversity in relation to skills within entrepreneurial teams (Sundermeier and Mahlert, 2022; Villani et al., 2018). Second, while 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; Fuentelsaz et al., 2023), industry experience (Becker-Blease and Sohl, 2015), previous occupational characteristics and experiences (Wu et al., 2023) or leadership experience (Hoenig and Henkel, 2015), this article adopt a skill-based approach and derived an outcome-based human capital indicator based on skills endorsement data which is considered a more direct measure of human capital and as one way of analyzing how skills affect firms' performance in a digital environment (Colombo, 2021; Drover et al., 2017; Klein et al., 2020; Marvel et al., 2016). Indeed, previous empirical studies often used raw measures of human capital, such as years of education, entrepreneurial experiences, or professional experiences, leading to insufficient precision of independent variables used to represent the variables of outcome of human capital (Harrison and Klein, 2007). In this study, we focuses on the 'outcomes of human capital' (i.e. knowledge, skills and abilities) as a complementary measure to those related to 'investment in human capital' such as education and experience. To do so, we make use of CrunchBase and LinkedIn and demonstrate the value of the data for research to understand the dynamics of signals in entrepreneurship literature. We acknowledge that the public nature of LinkedIn skill endorsements and the elements of performativity and reciprocation inherent in them may introduce potential bias (Pérez-Rosés et al., 2016). However, we posit that despite this potential bias, the use of online skill endorsements as a measure of human capital remains valid given their wide acceptance and usage in the professional world (Pérez-Rosés et al., 2016; Gasiorowski and Lee, 2022).

Nonetheless, our study is not without limitations, paving the way for future research opportunities. For instance, it would be beneficial to identify online skills endorsement effects on dependent variables such as start-ups' innovation performance over the life-cycle of the organization (Knight et al., 2020). Additionally, a larger sample size from different geographies or sectors could be used to augment the generalizability of the findings. Finally, an examination of the impact of online skills endorsement on funds raised in later stages of fundraising, and an effective measurement of the number of conflicts that arise in each start-up depending on its group composition, could enhance our understanding of the significance of group dynamics in signaling trust to investors.

References

R. Aggarwal, D. Kryscynski, and H. Singh. Evaluating venture technical competence in venture capitalist investment decisions. *Management Science*, 61(11):2685–2706, 2015.

G. K. Ahlers, D. Cumming, C. Günther, and D. Schweizer. Signaling in equity crowdfunding. *Entrepreneurship theory and practice*, 39(4):955–980, 2015.

W. R. Ashby. An introduction to cybernetics. 1957.

D. B. Audretsch and R. Thurik. Linking entrepreneurship to growth. 2001.

E. Autio. Entrepreneurship support in europe: Trends and challenges for eu policy. *London, England: Imperial College Business School*, 2016.

D. Banerji and T. Reimer. Startup founders and their linkedin connections: Are well-connected entrepreneurs more successful? *Computers in Human Behavior*, 90: 46–52, 2019.

J. A. Baum and B. S. Silverman. Picking winners or building them? alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. *Journal of business venturing*, 19(3):411–436, 2004.

R. C. Becherer and J. G. Maurer. The proactive personality disposition and entrepreneurial behavior among small company presidents. *Journal of small business management*, 37(1):28, 1999.

G. S. Becker. *Human capital.* University of Chicago press, 1964.

J. R. Becker-Blease and J. E. Sohl. New venture legitimacy: the conditions for angel investors. *Small Business Economics*, 45(4):735–749, 2015.

C. M. Beckman, M. D. Burton, and C. O'Reilly. Early teams: The impact of team demography on vc financing and going public. *Journal of business venturing*, 22 (2):147–173, 2007.

S. Bernstein, A. Korteweg, and K. Laws. Attracting early-stage investors: Evidence from a randomized field experiment. *The Journal of Finance*, 72(2):509–538, 2017.

T. Biemann and E. Kearney. Size does matter: How varying group sizes in a sample affect the most common measures of group diversity. *Organizational research methods*, 13(3):582–599, 2010.

P. Bourdieu. *La distinction. Critique sociale du jugement.* HÉditions de Minuit,, 1979.

G. N. Chandler and S. H. Hanks. Founder competence, the environment, and venture performance. *Entrepreneurship theory and practice*, 18(3):77–89, 1994.

X.-P. Chen, X. Yao, and S. Kotha. Entrepreneur passion and preparedness in business plan presentations: a persuasion analysis of venture capitalists' funding decisions. *Academy of Management journal*, 52(1):199–214, 2009.

M. G. Colombo and L. Grilli. Founders' human capital and the growth of new technology-based firms: A competence-based view. *Research policy*, 34(6):795–816, 2005.

O. Colombo. The use of signals in new-venture financing: A review and research agenda. *Journal of Management*, 47(1):237–259, 2021.

B. L. Connelly, S. T. Certo, R. D. Ireland, and C. R. Reutzel. Signaling theory: A review and assessment. *Journal of management*, 37(1):39–67, 2011.

C. Constantinov, P. Ş. Popescu, C. M. Poteraş, and M. L. Mocanu. Preliminary results of a curriculum adjuster based on professional network analysis. In *2015 19th International Conference on System Theory, Control and Computing (ICSTCC)*, pages 860–865. IEEE, 2015.

A. C. Cooper, F. J. Gimeno-Gascon, and C. Y. Woo. Initial human and financial capital as predictors of new venture performance. *Journal of business venturing*, 9 (5):371–395, 1994.

C. Courtney, S. Dutta, and Y. Li. Resolving information asymmetry: Signaling, endorsement, and crowdfunding success. *Entrepreneurship Theory and Practice*, 41 (2):265–290, 2017.

F. Delmar and S. Shane. Does experience matter? the effect of founding team experience on the survival and sales of newly founded ventures. *Strategic Organization*, 4(3):215–247, 2006.

M. C. Díaz-Fernández, M. R. González-Rodríguez, and B. Simonetti. Top management team diversity and high performance: An integrative approach based on upper echelons and complexity theory. *European Management Journal*, 38(1):157–168, 2020.

G. Drakopoulos, E. Kafeza, P. Mylonas, and H. Al Katheeri. Building trusted startup teams from linkedin attributes: A higher order probabilistic analysis. In *2020 IEEE 32nd International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 867–874. IEEE, 2020.

W. Drover, L. Busenitz, S. Matusik, D. Townsend, A. Anglin, and G. Dushnitsky. A review and road map of entrepreneurial equity financing research: venture capital, corporate venture capital, angel investment, crowdfunding, and accelerators. *Journal of management*, 43(6):1820–1853, 2017.

K. A. Eddleston, J. J. Ladge, C. Mitteness, and L. Balachandra. Do you see what i see? signaling effects of gender and firm characteristics on financing entrepreneurial ventures. *Entrepreneurship Theory and Practice*, 40(3):489–514, 2016.

K. M. Eisenhardt and C. B. Schoonhoven. Organizational growth: Linking founding team, strategy, environment, and growth among us semiconductor ventures, 1978-1988. *Administrative science quarterly*, pages 504–529, 1990.

F. Errico, A. Messeni Petruzzelli, U. Panniello, and A. Scialpi. Source of funding and specialized competences: the impact on the innovative performance of start-ups. *Journal of Knowledge Management*, 2023.

European-Commission. 'digital transformation of european industry and enterprises' – report from the strategic policy forum on digital entrepreneurship. *Report from the Strategic Policy Forum*, pages 1–14, 2015.

M. Ferrary. Confiance et accumulation de capital social dans la régulation des activités de crédit. *Revue française de sociologie*, pages 559–586, 1999.

N. Franke, M. Gruber, D. Harhoff, and J. Henkel. What you are is what you like—similarity biases in venture capitalists' evaluations of start-up teams. *Journal of Business Venturing*, 21(6):802–826, 2006.

N. Franke, M. Gruber, D. Harhoff, and J. Henkel. Venture capitalists' evaluations of start–up teams: Trade–offs, knock–out criteria, and the impact of vc experience. *Entrepreneurship Theory and Practice*, 32(3):459–483, 2008.

L. Fuentelsaz, C. González, and T. Mickiewicz. Entrepreneurial growth aspirations at re-entry after failure. *International Journal of Entrepreneurial Behavior & Research*, 29(2):297–327, 2023.

L. Gasiorowski and A. Lee. Pay attention to me! the role of endorsements, patents, gender and prior experience in startup media attention. *Journal of Small Business and Enterprise Development*, 30(1):120–143, 2022.

M. M. Ghassemi, C. Song, and T. Alhanai. The automated venture capitalist: Data and methods to predict the fate of startup ventures. 2015.

T. Harrer and R. Owen. Reducing early-stage cleantech funding gaps: an exploration of the role of environmental performance indicators. *International Journal of Entrepreneurial Behavior & Research*, 28(9):268–288, 2022.

D. A. Harrison and K. J. Klein. What's the difference? diversity constructs as separation, variety, or disparity in organizations. *Academy of management review*, 32(4):1199–1228, 2007.

D. Hoenig and J. Henkel. Quality signals? the role of patents, alliances, and team experience in venture capital financing. *Research Policy*, 44(5):1049–1064, 2015.

L. Hong and S. E. Page. Problem solving by heterogeneous agents. *Journal of economic theory*, 97(1):123–163, 2001.

D. H. Hsu. Experienced entrepreneurial founders, organizational capital, and venture capital funding. *Research policy*, 36(5):722–741, 2007.

L. Huang and A. P. Knight. Resources and relationships in entrepreneurship: An exchange theory of the development and effects of the entrepreneur-investor relationship. *Academy of Management Review*, 42(1):80–102, 2017.

J. E. Hunter. Cognitive ability, cognitive aptitudes, job knowledge, and job performance. *Journal of vocational behavior*, 29(3):340–362, 1986.

M. Islam, A. Fremeth, and A. Marcus. Signaling by early stage startups: Us government research grants and venture capital funding. *Journal of Business Venturing*, 33(1):35–51, 2018.

G. James, D. Witten, T. Hastie, and R. Tibshirani. *An introduction to statistical learning*, volume 112. Springer, 2013.

J. J. Janney and T. B. Folta. Moderating effects of investor experience on the signaling value of private equity placements. *Journal of Business Venturing*, 21(1):27–44, 2006.

L. Jin, K. Madison, N. D. Kraiczy, F. W. Kellermanns, T. R. Crook, and J. Xi. Entrepreneurial team composition characteristics and new venture performance: A meta–analysis. *Entrepreneurship Theory and Practice*, 41(5):743–771, 2017.

H. Jung, B. Vissa, and M. Pich. How do entrepreneurial founding teams allocate task positions? *Academy of Management Journal*, 60(1):264–294, 2017.

S. N. Kaplan, B. A. Sensoy, and P. Strömberg. Should investors bet on the jockey or the horse? evidence from the evolution of firms from early business plans to public companies. *The Journal of Finance*, 64(1):75–115, 2009.

N. Kaushal, R. P. S. Kaurav, B. Sivathanu, and N. Kaushik. Artificial intelligence and hrm: identifying future research agenda using systematic literature review and bibliometric analysis. *Management Review Quarterly*, pages 1–39, 2021.

F. Kirschenhofer and C. Lechner. Performance drivers of serial entrepreneurs: Entrepreneurial and team experience. *International Journal of Entrepreneurial Behavior & Research*, 18(3):305–329, 2012.

J. Kirtley and S. O'Mahony. What is a pivot? explaining when and how entrepreneurial firms decide to make strategic change and pivot. *Strategic Management Journal*, 2020.

M. Klein, F. Neitzert, T. Hartmann-Wendels, and S. Kraus. Start-up financing in the digital age–a systematic review and comparison of new forms of financing. *The Journal of Entrepreneurial Finance*, 21(2):3, 2020.

A. C. Klotz, K. M. Hmieleski, B. H. Bradley, and L. W. Busenitz. New venture teams: A review of the literature and roadmap for future research. *Journal of management*, 40(1):226–255, 2014.

A. P. Knight, L. L. Greer, and B. De Jong. Start-up teams: A multidimensional conceptualization, integrative review of past research, and future research agenda. *Academy of Management Annals*, 14(1):231–266, 2020.

E.-J. Ko and A. McKelvie. Signaling for more money: The roles of founders' human capital and investor prominence in resource acquisition across different stages of firm development. *Journal of Business Venturing*, 33(4):438–454, 2018.

J. B. Kruskal. On the shortest spanning subtree of a graph and the traveling salesman problem. *Proceedings of the American Mathematical society*, 7(1):48–50, 1956.

M. R. Marvel and G. T. Lumpkin. Technology entrepreneurs' human capital and its effects on innovation radicalness. *Entrepreneurship Theory and Practice*, 31(6): 807–828, 2007.

M. R. Marvel, J. L. Davis, and C. R. Sproul. Human capital and entrepreneurship research: A critical review and future directions. *Entrepreneurship Theory and Practice*, 40(3):599–626, 2016.

S. F. Matusik, J. M. George, and M. B. Heeley. Values and judgment under uncertainty: evidence from venture capitalist assessments of founders. *Strategic Entrepreneurship Journal*, 2(2):95–115, 2008.

M. Milosevic. Skills or networks? success and fundraising determinants in a low performing venture capital market. *Research Policy*, 47(1):49–60, 2018.

E. Mollick. The dynamics of crowdfunding: An exploratory study. *Journal of business venturing*, 29(1):1–16, 2014.

S. Nambisan. Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice*, 41(6):1029–1055, 2017.

B. Nooteboom, W. Van Haverbeke, G. Duysters, V. Gilsing, and A. Van den Oord. Optimal cognitive distance and absorptive capacity. *Research policy*, 36(7):1016–1034, 2007.

K. A. Packalen. Complementing capital: The role of status, demographic features, and social capital in founding teams' abilities to obtain resources. *Entrepreneurship Theory and Practice*, 31(6):873–891, 2007.

H. Pérez-Rosés, F. Sebé, and J. M. Ribó. Endorsement deduction and ranking in social networks. *Computer Communications*, 73:200–210, 2016.

J. R. Pierce and H. Aguinis. The too-much-of-a-good-thing effect in management. *Journal of Management*, 39(2):313–338, 2013.

L. A. Plummer, T. H. Allison, and B. L. Connelly. Better together? signaling interactions in new venture pursuit of initial external capital. *Academy of Management Journal*, 59(5):1585–1604, 2016.

M. C. U. Ponte, A. Méndez-Zorrilla, and I. O. Ruiz. Use of linkedin endorsements in recommender systems. *Education and New Developments*, 115, 2022.

C. Rapanta and L. Cantoni. The linkedin endorsement game: Why and how professionals attribute skills to others. *Business and Professional Communication Quarterly*, 80(4):443–459, 2017.

D. Reese, V. Rieger, and A. Engelen. Should competencies be broadly shared in new ventures' founding teams? *Strategic Entrepreneurship Journal*, 2020.

N. Rosenbusch, J. Brinckmann, and V. Müller. Does acquiring venture capital pay off for the funded firms? a meta-analysis on the relationship between venture capital investment and funded firm financial performance. *Journal of business venturing*, 28(3):335–353, 2013.

J. B. Roure and R. H. Keeley. Predictors of success in new technology based ventures. *Journal of business venturing*, 5(4):201–220, 1990.

M. Sako, M. Qian, M. Verhagen, and R. Parnham. Scaling up firms in entrepreneurial ecosystems: Fintech and lawtech ecosystems compared. *Available at SSRN 3520533*, 2020.

S. Seabold and J. Perktold. statsmodels: Econometric and statistical modeling with python. In *9th Python in Science Conference*, 2010.

T. Semrau and A. Werner. How exactly do network relationships pay off? the effects of network size and relationship quality on access to start–up resources. *Entrepreneurship Theory and Practice*, 38(3):501–525, 2014.

S. Shane and D. Cable. Network ties, reputation, and the financing of new ventures. *Management science*, 48(3):364–381, 2002.

S. Shane and T. Stuart. Organizational endowments and the performance of university start-ups. *Management science*, 48(1):154–170, 2002.

S. Shane and S. Venkataraman. The promise of entrepreneurship as a field of research. *Academy of management review*, 25(1):217–226, 2000.

M. Spence. *Market signaling: Informational transfer in hiring and related screening processes*. Number 143. cambridge: harvard university press, 1974.

M. Spence. Job market signaling. In *Uncertainty in economics*, pages 281–306. Elsevier, 1978.

M. Spence. Signaling in retrospect and the informational structure of markets. *American economic review*, 92(3):434–459, 2002.

H. C. Subramanian, V. Venkataraman, and H. Jiang. Backing the right jockey? founder traits and early-stage funding in digital entrepreneurship. In *Academy of Management Proceedings*, volume 2022, page 17128. Academy of Management Briarcliff Manor, NY 10510, 2022.

J. Sundermeier and N. Mahlert. Entrepreneurial team diversity–a systematic review and research agenda. *European Management Journal*, 2022.

D. M. Townsend and L. W. Busenitz. Turning water into wine? exploring the role of dynamic capabilities in early-stage capitalization processes. *Journal of Business Venturing*, 30(2):292–306, 2015.

M. C. Urdaneta-Ponte, A. Méndez-Zorrilla, and I. Oleagordia-Ruiz. Lifelong learning courses recommendation system to improve professional skills using ontology and machine learning. *Applied Sciences*, 11(9):3839, 2021.

E. Villani, C. Linder, and C. Lechner. Entrepreneurial team composition and strategic choice: A configurational analysis. In *Academy of Management Proceedings*, volume 2018, page 13498. Academy of Management Briarcliff Manor, NY 10510, 2018.

O. Williamsky. Demography and diversity in organizations: A review of 40 years of research. *Research in Organizational Behavior*, 20(3):77–140, 1998.

Y. Wu, N. Dhakal, D. Xu, and J.-H. Cho. Analysis and prediction of endorsement-based skill assessment in linkedin. In *2018 IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC)*, volume 1, pages 461–470. IEEE, 2018.

Y. Wu, G. Maas, Y. Zhang, F. Chen, S. Xia, K. Fernandes, and K. Tian. The secrets to successful entrepreneurship: how occupational experience shapes the creation and performance of start-ups. *International Journal of Entrepreneurial Behavior & Research*, 29(2):354–384, 2023.

X. Yan, J. Yang, M. Obukhov, L. Zhu, J. Bai, S. Wu, and Q. He. Social skill validation at linkedin. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 2943–2951, 2019.

W. Zhou and E. Rosini. Entrepreneurial team diversity and performance: Toward an integrated model. *Entrepreneurship Research Journal*, 5(1):31–60, 2015.

7 Annexes

Table 1: Variable definitions and sources

Variable name	Description	Data source
Dependent variable		
1. *Capital Raised (log)*	Natural logarithm of the amount of investment provided by external investors in the first round [€]	Crunchbase, BPI
Independent variables		
2. *Skills level*	Ordinate variable ranging from 0 to 9 (0= min; 9= max). Each start-up team is assigned the highest median score associated with any of its members	Linkedin
3. *Skills field variety*	Blau index on the probability of finding a particular skill in a start-up team among the six fields identified (i.e., Finance, Product, Development, Management, Marketing, Entrepreneurship)	Linkedin
Control variables		
Human Capital control variables		
4. *Previous Prestigious University*	Number of graduations from one of the best French business, engineering schools or from the 10 universities worldwide. Each start-up team is assigned the maximum score associated with any of its members	LinkedIn
5. *Previous Founding Experience*	Number of unique ventures previously founded or co-founder. Each start-up team is assigned the maximum score associated with any of its members	LinkedIn
6. *Previous Working Experience*	Maximum number of years of work experience of a start-up team member. Each start-up team in our sample is assigned the highest score associated with any of its members	LinkedIn
7. *Previous Ph.D Degree*	Number of Ph.D graduations. Each start-up team is assigned the maximum score associated with any of its members	LinkedIn
New Ventures control variables		
8. *New Venture Age*	Number of years since new ventures' foundation	Crunchbase, BPI
9. *Team size*	Number of start-up team members	LinkedIn
10. *Industry*	Eleven industry dummies which take value 1 if the company is operating in i) Business Intelligence Analytics, ii) Customer Relationship Management, iii) Developers Software Infrastructure, iv) Education Human Resources, v) Finance Legal Insurance, vi) Healthcare, vii) Logistics Supply Chain, viii) Marketing and Media ix) Productivity Collaboration, x) Real Estate Construction xi) Retail Ecommerce	Crunchbase, BPI

Table 2: Distribution of sample : digital new ventures by industry classification

Industry	Number of firms	% total
Business Intelligence Analytics	38	8.7
Customer Relationship Management	25	5.7
Developers Software Infrastructure	50	11.4
Education Human Resources	59	13.4
Finance Legal Insurance	51	11.6
Healthcare	24	5.5
Logistics Supply Chain	27	6.1
Marketing and Media	56	12.8
Productivity Collaboration	48	10.9
Real Estate Construction	25	5.7
Retail Ecommerce	36	8.2
Total	439	100

Table 3: Descriptive statistics of fundraising rounds

Part A : Fundraising rounds per years	Amount in millions of euros					
Fundraising years	Rounds	Mean	Median	Min	Max	SD
2011	4	0.251	0.115	0.025	0.750	0.338
2012	7	0.977	0.700	0.100	2.500	0.878
2013	19	0.611	0.200	0.060	5.000	1.114
2014	30	0.752	0.370	0.055	8.000	1.457
2015	54	1.146	0.500	0.023	10.000	1.783
2016	56	0.942	0.400	0.060	12.000	1.689
2017	67	1.542	0.750	0.050	10.000	2.090
2018	44	1.796	1.000	0.090	15.000	2.544
2019	38	2.044	1.500	0.250	12.000	2.131
2020	11	2.410	1.000	0.500	14.500	4.073
Total	330	1.247	0.600	0.023	15.000	1.027

Part B : Fundraising per founding date		Amount in millions of euros					
Founding date	Firms	Rounds	Mean	Median	Min	Max	SD
2011	27	27	1.196	0.400	0.250	7.300	1.564
2012	36	29	0.834	0.450	0	4.000	1.040
2013	58	49	0.775	0.250	0	8.000	1.447
2014	65	49	1.415	0.300	0	15.000	2.864
2015	74	55	1.141	0.400	0	14.500	2.331
2016	85	67	0.067	0.500	0	12.000	1.856
2017	60	35	0.679	0.215	0	3.700	0.925
2018	34	19	0.828	0.550	0	4.000	1.035
Total	439	330	0.992	0.400	0	15.000	0.687

Table 4: Descriptive statistics

Variables	Obs	Mean	SD	Min	Max
Dependent variable					
Capital Raised (log)	439	10.009	5.872	0	16.524
Independent variables					
Skills level	439	6.215	2.186	0	9
Skills field variety	439	0.621	0.354	0	1
Control variables					
Human capital control variables					
Previous Prestigious University	439	0.827	0.766	0	3
Previous Founding Experience	439	1.230	0.981	0	4
Previous Working Experience	439	16.724	8.629	1	47
Previous PhD Degree	439	0.128	0.360	0	2
Firms control variables					
New Venture Age	439	5.205	1.950	2	9
Team size	439	2.590	0.785	2	8
Business Intelligence Analytics	439	0.087	0.282	0	1
Customer Relationship Management	439	0.057	0.232	0	1
Developers Software Infrastructure	439	0.114	0.318	0	1
Education Human Resources	439	0.134	0.341	0	1
Finance Legal Insurance	439	0.116	0.321	0	1
Healthcare	439	0.055	0.228	0	1
Logistics Supply Chain	439	0.062	0.241	0	1
Productivity Collaboration	439	0.109	0.312	0	1
Real Estate Construction	439	0.057	0.232	0	1
Marketing Media	439	0.128	0.334	0	1
Retail Ecommerce	439	0.082	0.275	0	1

Table 5: Correlation Table

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Capital Raised (log)	1																		
2	Skills level	0.142	1																	
3	Skills field variety	-0.018	-0.257	1																
4	Previous Prestigious University	0.213	0.031	0.020	1															
5	Previous Founding Experience	0.124	0.151	-0.079	0.065	1														
6	Previous Working Experience	0.073	0.260	-0.144	-0.046	0.163	1													
7	Previous PhD Degree	0.005	-0.148	0.080	0.089	-0.025	0.052	1												
8	Firm Age	0.189	0.241	-0.165	-0.013	0.034	0.273	-0.005	1											
10	Team Size	0.088	0.180	0.168	0.163	0.152	0.156	0.016	-0.122	1										
11	Business Intelligence Analytics	-0.033	-0.038	0.002	0.059	-0.122	0.025	0.026	0.130	-0.025	1									
10	Customer Relationship Management	-0.001	0.111	-0.135	0.004	0.033	0.038	-0.060	0.120	-0.047	-0.076	1								
11	Developers Software Infrastructure	0.050	-0.144	0.101	-0.022	0.004	0.157	0.112	0.040	-0.005	-0.110	-0.088	1							
12	Education Human Resources	0.023	0.082	-0.058	-0.068	-0.045	-0.078	-0.028	-0.100	0.053	-0.121	-0.097	-0.141	1						
13	Finance Legal Ins"urance	0.042	-0.076	0.067	0.045	0.125	-0.002	-0.069	-0.166	0.026	-0.112	-0.089	-0.130	-0.143	1					
14	Healthcare	0.070	-0.054	0.041	0.133	0.036	0.050	0.221	-0.041	0.049	-0.074	-0.059	-0.086	-0.095	-0.087	1				
15	Logistics Supply Chain	-0.009	0.053	0.049	-0.041	-0.041	-0.025	-0.012	-0.027	0.098	-0.079	-0.063	-0.092	-0.101	-0.093	-0.062	1			
16	Productivity Collaboration	-0.065	0.014	0.026	-0.026	0.037	-0.063	-0.104	-0.011	-0.112	-0.108	-0.086	-0.126	-0.138	-0.127	-0.084	-0.090	1		
17	Real Estate Construction	0.003	-0.062	-0.002	0.004	-0.068	-0.021	-0.087	-0.076	-0.034	-0.076	-0.060	-0.088	-0.097	-0.089	-0.059	-0.063	-0.086	1	
18	Marketing Media	-0.074	0.045	-0.014	-0.056	-0.006	-0.027	0.016	0.033	-0.044	-0.118	-0.094	-0.137	-0.151	-0.139	-0.092	-0.098	-0.134	-0.094	1
19	Retail Ecommerce	0.011	0.079	-0.100	0.013	0.031	-0.038	0.009	0.131	-0.055	-0.092	-0.073	-0.107	-0.118	-0.108	-0.072	-0.077	-0.105	-0.073	-0.114

Table 6: Results of OLS Regression for Signals and Investment Outcome. Log of funds received is the dependent variable of the OLS linear regression.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Theorical					
Skill level (SL)		0.250* (0.139)		0.265* (0.143)	0.547*** (0.192)
Skill field diversity (SFD)			0.005 (0.810)	0.369 (0.831)	4.575** (2.104)
Interaction SL * SFD					-1.051** (0.484)
Controls					
Previous Prestigious University	1.509*** (0.364)	1.477*** (0.363)	1.509*** (0.364)	1.480*** (0.364)	1.478*** (0.362)
Previous Founding Experience	0.527* (0.286)	0.481* (0.286)	0.527* (0.287)	0.489* (0.287)	0.463 (0.286)
Previous Working Experience	-0.008 (0.034)	-0.021 (0.035)	-0.007 (0.035)	-0.020 (0.035)	-0.020 (0.035)
Previous PhD Degree	-0.374 (0.780)	-0.168 (0.787)	-0.374 (0.783)	-0.179 (0.788)	-0.256 (0.785)
Firm Age	0.689*** (0.152)	0.637*** (0.154)	0.689*** (0.152)	0.638*** (0.154)	0.655*** (0.154)
Team Size	0.451 (0.363)	0.346 (0.367)	0.451 (0.370)	0.308 (0.377)	0.213 (0.378)
Business Intelligence Analytics	-0.741 (1.317)	-0.521 (1.319)	-0.741 (1.322)	-0.549 (1.322)	-0.650 (1.317)
Customer Relationship Management	-0.309 (1.466)	-0.352 (1.462)	-0.309 (1.468)	-0.336 (1.464)	-0.347 (1.458)
Developers Software Infrastructure	1.231 (1.248)	1.613 (1.263)	1.230 (1.262)	1.555 (1.271)	1.578 (1.265)
Education Human Resources	1.298 (1.209)	1.269 (1.206)	1.298 (1.211)	1.261 (1.207)	1.320 (1.202)
Finance Legal Insurance	1.350 (1.256)	1.583 (1.259)	1.349 (1.264)	1.537 (1.265)	1.478 (1.259)
Healthcare	1.704 (1.521)	1.927 (1.522)	1.703 (1.528)	1.889 (1.526)	1.607 (1.525)
Logistics Supply Chain	0.477 (1.449)	0.492 (1.446)	0.477 (1.455)	0.446 (1.451)	0.432 (1.444)
Marketing Media	-0.610 (1.206)	-0.564 (1.203)	-0.610 (1.209)	-0.594 (1.206)	-0.625 (1.201)
Productivity Collaboration	-0.633 (1.249)	-0.531 (1.247)	-0.634 (1.255)	-0.571 (1.252)	-0.696 (1.247)
Intercept	3.109*** (1.610)	2.261 (1.673)	3.107* (1.666)	2.018 (1.762)	0.481 (1.891)
R-squared	0.119	0.126	0.119	0.126	0.136
R-squared Adj.	0.086	0.091	0.084	0.089	0.097
Observations	439	439	439	439	439

SEs are in parentheses
*** $p < .001$; ** $p < .01$; * $p < .05$

Table 7: Results of Logit Regression for Signals and Investment Outcome. Fundraising is the dependent variable of the Logit regression.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Theorical					
Skill level (SL)		0.105*		0.109*	0.224***
		(0.060)		(0.061)	(0.086)
Skill field diversity (SFD)			-0.005	0.135	1.801*
			(0.365)	(0.375)	(0.942)
Interaction SL * SFD					-0.424*
					(0.219)
Controls					
Previous Prestigious University	0.720***	0.705***	0.720***	0.704***	0.709***
	(0.179)	(0.179)	(0.179)	(0.179)	(0.180)
Previous Founding Experience	0.187	0.167	0.187	0.169	0.176
	(0.130)	(0.131)	(0.130)	(0.131)	(0.132)
Previous Working Experience	-0.015	-0.021	-0.015	-0.021	-0.022
	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)
Previous PhD Degree	-0.140	-0.071	-0.140	-0.074	-0.105
	(0.351)	(0.354)	(0.351)	(0.354)	(0.352)
Firm Age	0.371***	0.350***	0.371***	0.350***	0.366***
	(0.073)	(0.074)	(0.073)	(0.074)	(0.075)
Team Size	0.246	0.202	0.247	0.187	0.156
	(0.170)	(0.172)	(0.174)	(0.176)	(0.178)
Business Intelligence Analytics	-0.410	-0.298	-0.409	-0.306	-0.340
	(0.583)	(0.589)	(0.584)	(0.589)	(0.592)
Customer Relationship Management	-0.131	-0.128	-0.131	-0.122	-0.083
	(0.658)	(0.659)	(0.659)	(0.660)	(0.667)
Developers Software Infrastructure	0.652	0.822	0.653	0.802	0.850
	(0.582)	(0.591)	(0.586)	(0.594)	(0.597)
Education Human Resources	0.573	0.575	0.573	0.578	0.643
	(0.550)	(0.551)	(0.550)	(0.551)	(0.556)
Finance Legal Insurance	0.514	0.657	0.515	0.635	0.636
	(0.574)	(0.582)	(0.579)	(0.585)	(0.587)
Healthcare	0.941	1.113	0.941	1.108	1.055
	(0.784)	(0.800)	(0.785)	(0.801)	(0.809)
Logistics Supply Chain	0.179	0.203	0.180	0.185	0.212
	(0.648)	(0.652)	(0.650)	(0.654)	(0.658)
Marketing Media	-0.275	-0.227	-0.275	-0.241	-0.249
	(0.531)	(0.534)	(0.533)	(0.535)	(0.536)
Productivity Collaboration	-0.306	-0.255	-0.305	-0.271	-0.304
	(0.543)	(0.543)	(0.545)	(0.545)	(0.546)
Intercept	-1.989***	-2.350***	-1.987***	-2.428***	-3.104***
	(0.743)	(0.773)	(0.762)	(0.804)	(0.884)
Observations	439	439	439	439	439

SEs are in parentheses
*** $p < .001$; ** $p < .01$; * $p < .05$

Table 8: Main odds Ratio of the Logit regression.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Theorical					
Skill level (SL)		1.110		1.115	0.044
Skill field diversity (SFD)			0.995	1.144	6.057
Interaction SL * SFD					0.654
Intercept	0.136	0.095	0.137	0.088	0.044
Observations	439	439	439	439	439