Jack of All Trades vs Master of Some: Searching Ideal Knowledge Portfolio for Tech Start-Ups

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ABSTRACT

Senior leadership is indisputably central to firm performance. Numerous studies have delved into various attributes of firm leadership as predictors of performance, primarily focusing on educational background and prior tenure in other organizations. Surprisingly, the role of technical skills within firm leaders remains an under-researched area. Given that these leaders often serve as chief decision-makers in technology-centric firms, managing numerous engineers, their technical skills likely play a crucial role in ensuring seamless operations and fostering productive teams. This study addresses this gap by examining the influence of leaders' technical skills, specifically evaluating the diversity of these skills, and their depth and breadth within each technical domain on firm performance. Using data from Angel.co and LinkedIn, we constructed technical profiles for 100 firms based on the technical skills of their founders. Our analysis focused on the relationship between the Euclidean distance of technical profiles, their breadth and depth, and firm performance was measured in terms of the capital raised. Our findings suggest that the diversity and depth of technical profiles affect firm performance. We further discuss the broader implications of our results for both research and practical application.

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INTRODUCTION

Innovations in IT continue to have major financial and societal implications. As of 2023, 7 of the 10 largest companies by market value in the world are tech companies (Pinkerton, 2023). Technology start-ups play a critical role in accelerating innovation. One of their most common approaches to accelerate innovation by acquiring resourceful employees and technology by acquiring or partnering with start-ups that develop them. Such acquisitions and partnerships include Google taking over smaller IoT start-ups like Xively (Miller, 2018) and NEST (Nicas, 2017). Most recently, Microsoft partnered with OpenAI for integrating generative artificial intelligence in their platforms (Microsoft Corporate Blogs, 2023).

Technology start-ups rely on their innovation more than their bigger counterparts. The process of innovation in start-ups is fundamentally different from bigger companies. They face higher risk of survival compared to more established firms (MacMillan et al., 1987). They also face threats of newness and smallness due to their unknown nature, lack of business history and lack of access to financial capital (Havakhor, 2016; Leung et al., 2006). In early stages, these companies constitute an average of 11-50 employees. They rely heavily on skills and abilities of their founders and employees due to their disproportionate amount of personal and financial investment. Even though these small companies face many challenges, they contribute substantially through innovation and its diffusion across diverse lines of products. One of the major goals of start-ups is to raise capital. Total capital raised is the value, the company has generated using venture capitalists. In this research, we define a startup as a newly founded company with an innovative business idea, often seeking rapid growth and typically characterized by limited operating history and resources (Cockayne, 2019).

Consistent with upper echelon's theory, in technology startups, founders often stand out as the key drivers for attracting investments (Hambrick & Mason, 1984; Yamak et al., 2014). Due to their unique technical skills and expertise, founders in technology startups possess a deeper understanding of the venture's technical intricacies, arising from their pivotal role in conceiving and nurturing the technology-driven idea from its inception. This profound understanding engenders trust and confidence among potential investors, who are drawn to the founders' technical prowess, visionary leadership, and entrepreneurial acumen, particularly in the fast-paced tech industry (Patzelt et al., 2009). Furthermore, the founders' unwavering commitment to the startup's mission and their readiness to shoulder personal and financial risks create a compelling alignment of interests with investors. Nonetheless, it's important to note that while founders play a central role, a well-rounded, diverse team can complement their technical expertise and enhance the overall appeal to investors in the technology sector. While there are significant networking effects (such as pre-existing relationships with venture capitalists), the technical skills of founders in technology startups are pivotal in attracting investments (Marvel et al., 2020). Founders play a central role in generating ideas and strategies for a technology start-up. Analogical reasoning theory and agglomeration theory provide insights into how they can effectively activate and recombine their knowledge at firm level to propose novel solutions in the technology sector.

Knowledge agglomeration theory suggests that diverse technical skills among founders influence capital raising while analogical reasoning theory explores how individuals use their knowledge to generate novel ideas, emphasizing their ability to activate and recombine information. Extensive research has explored individual idea generation. Firm level idea generation and implementation has not been investigated at a noteworthy extent. This presents an intriguing gap in the literature, as it could provide insights into how organizations leverage collective knowledge for innovation and idea generation, ultimately enhancing our understanding of how firms adapt and innovate in dynamic business environments. Total capital raised often serves as a good proxy for the quality of a startup's ideas because it reflects investor confidence, market validation, competitive advantage, execution capability, scalability potential, and network effects associated with high-quality ideas. To address this gap in literature, in this research, we explore the following research question:

RQ: How do the specific technical skills of startup founders (in terms of their breadth, depth, and diversity from peer startups) influence the amount of capital they are able to raise?

To address our research question, we present a novel measurement for evaluating the knowledge base of technology startups. Using data from Angel.co and LinkedIn, we constructed technical profiles for 100 firms based on the technical skills of their founders. Our analysis focused on the relationship between the Euclidean distance of technical profiles, their breadth and depth, and firm performance was measured in terms of the capital raised. Our findings suggest that the diversity and depth of technical profiles affect firm performance. Understanding the effects of structure knowledge networks can have implications of recruitment and selection of employees for technical development-centric jobs.

THEORETICAL BACKGROUND

Three theories inform our investigation of the research question posed above: Upper Echelons Theory, agglomeration theory, and analogical reasoning theory. We use these theories to connect individual level variables such as technical skills to firm level investigation as required by our research question.

Upper echelon theory explains the link between founders and key initial employees' traits (such as technical skills) and the firm's performance. In this research, we measure firm performance in terms of total capital raised. Consistent with prior literature, total capital raised is a key indicator of performance for startups as money raised in initial rounds is critical for their survival (Haw et al., 2000; Kim et al., 1993; Short et al., 2017) .

Analogical reasoning theory explains how novel ideas are a function of an individual's breadth and depth of their knowledge. Our research attempts to combine upper echelon's theory and analogical reasoning theory and show how combined knowledge of founders and key employees make up the knowledge profile for the start-up in initial stages.

Additionally, we also study the knowledge profiles with theoretical lens of agglomeration. Knowledge agglomeration refers to the concentration of expertise and resources in specific fields. Researchers, institutions, large organizations, and start-ups globally can agglomerate around particular topics such as AI or IoT. This can lead to firms having founders and employees with similar skills. Having people with similar skills can have competing effects. It can be beneficial for a start-up to have people with similar skills as that of peer start-ups to leverage shared ideas and ride benefit from market inertia. Thus, bolstering their capability to attract capital. Conversely, it can also have a negative effect on firms as they might face increased competition in a red ocean market. Hence, they may not be able to attract capital. The following sections discuss brief overview and prior literature of each of these theories.

Upper Echelons Theory

Upper Echelons Theory (UET) posits that the experiences, values, personalities, and cognitive foundations of top executives influence their interpretations, choices, and subsequently, organizational outcomes (Hambrick & Mason, 1984). UET has emerged as a highly influential perspective in the field of strategic management, inspiring research into how executives' characteristics and experiences shape their perceptions, choices, and actions, ultimately impacting various outcomes within organizations (Bromiley & Rau, 2016; Hodgkinson & Sparrow, 2002). A series of systematic reviews have evaluated the progress of UET research over the last two decades (Carpenter et al., 2004; Hambrick, 2007). Prior literature has confirmed this theory by examining individual-level variables like personality traits, such as extraversion, anarchism, and political views, to elucidate firm-level outcomes, including changes in Tobin's q and AI orientation (Hambrick, 2007; Lovelace et al., 2018).

UET offers valuable insights into the connection between the attributes of founders and key initial employees, especially their technical skills, and the overall performance of the firm. However, further research is needed to understand the mechanisms by which how traits like skills factor into a firm's performance. In a metacritique article that reviewed 35 years of research on Upper Echelons Theory, Neely et al. (2020) acknowledged research based on the theory's capacity to connect executive traits to distant firm outcomes but criticized it for often neglecting to explore the mediating process mechanisms, a limitation that some argue restricts its practical and conceptual contributions (Neely Jr et al., 2020) .

In this study, we assess firm performance using the metric of total capital raised, a critical indicator for the survival and growth of startups, particularly in the technology sector (Haw et al., 2000; Kim et al., 1993; Short et al., 2017). Our argument centers on the significance of technical proficiency among organizational leaders in tech-oriented startups, asserting that it plays a pivotal role in determining the firm's success and its capacity for innovation, a perspective corroborated by prior research (Brock & von Wangenheim, 2019; Karahanna & Preston, 2013; Li et al., 2021).

Analogical Reasoning Theory

Information systems initiation is viewed as capabilities enabling detection of opportunities in the external environment, such as technological opportunism capabilities and entrepreneurial alertness (Kohli & Melville, 2019). Previous firm-level research in IS innovation regarding initiation has centered around R&D output (Bloom et al., 2013). Individual-level innovation research has primarily studied idea-generation from an individual’s stock of knowledge (Hwang et al., 2019). Research has proposed that recombining existing knowledge in new ways leads to generation of novel ideas and solutions (Fleming, 2001; Hwang et al., 2019; Kulkarni & Simon, 1988). The ability of analogical reasoning relies on degree to which individuals can create ‘analogies’ i.e. activate the relevant areas of their knowledge to propose a novel idea or solution. Within individuals with same stock of knowledge, the ability to better activate and recombine known information differentiates innovative individuals from others. Structure Mapping through analogical reasoning has been used to explained the process of generation of novel ideas among individuals (Gentner, 1983). Firm level idea generation and implementation has not been investigated at a noteworthy extent.

Each technology-based firm is different and thus, requires a different technical profile of skills to lead them effectively. Innovation literature suggests that two types of information are critical to generation of a successful product idea: Needs and Means (Baker & Freeland, 1972), 'needs' refers to the knowledge of a need, problem, or opportunity 'means' refers to the knowledge for satisfying the need, solving the problem or capitalizing on the opportunity. For example, in 2011, ex-Apple employee and entrepreneur Tony Fadell realized the need for an easier-to-use programmable thermostat with better connectivity to smart devices. He subsequently founded Nest Labs, searched for funding and employees with skills who can develop the said thermostat. In this case, Fadell recognized a 'need', his and his team's knowledge network was the 'means' for an ultimately successful start-up that was acquired by Google for $3.2 billion (Team, 2014). The information network that recognizes the needs and means is a subset of an individual's entire stock of knowledge (Tsoukas, 1996). This information network carries over to firm level knowledge.

Prior research has evaluated information networks at the individual level, however, firm level effects of information networks are relatively understudied. In this research, we study firm level information network built from the skills of firm's leaders. Our focus is on technical skills, we refer to this subset of information network as a technical profile. Our research attempts to combine upper echelon's theory and analogical reasoning theory and show how combined knowledge of founders and key employees make up the knowledge profile for the start-up in initial stages.

Agglomeration Theory

Agglomeration theory explains the clustering of economic activities, such as businesses, industries, or institutions, in specific geographic areas or regions (Chu et al., 2019). However, as the belief in the diminishing importance of physical distance gained popularity towards the end of the 20th century, the role of non-geographic connections in innovation spillovers started to gain prominence (Ahn et al., 2009). Alongside geographic distance, factors such as social distance, cognitive distance, organizational distance, institutional distance, technological distance, and cultural distance have been identified as influencing innovation spillovers.

Ideally, firms working in the same industry have similar kind of labor. Knowledge agglomeration theory explains that businesses benefit from being collocated due to various efficiencies. Orlando (2004) showed that spillovers within narrowly defined, four-digit industrial classifications appear stronger than those in the broader three-digit categories. Interestingly, these narrow spillovers aren't diminished by geographic distance, suggesting that the very proximity or closeness doesn't necessarily weaken their impact. However, when we consider spillovers that cross the four-digit boundaries, geographic distance does seem to lessen their effect. This suggests that geographic distance might influence the formation of diverse industrial agglomerations, but only up to a certain threshold of diversity (Orlando, 2004).

We study the knowledge profiles with theoretical lens of agglomeration. Knowledge agglomeration refers to the concentration of expertise and resources in specific fields. Researchers, institutions, large organizations, and start-ups globally can agglomerate around particular topics such as AI or IoT (Kekezi & Klaesson, 2020). This can lead to firms having founders and employees with similar skills. Having people with similar skills can have competing effects. It can be beneficial for a start-up to have people with similar skills as that of peer start-ups to leverage shared ideas and ride benefit from market inertia. Thus, bolstering their capability to attract capital. Conversely, it can also have a negative effect on firms as they might face increased competition in a red ocean market. Hence, they may not be able to attract capital.

HYPOTHESES DEVELOPMENT

According to the Theory of Analogical Reasoning, individuals create new ideas by activating, adapting, and recombining knowledge. In this research, we extend this theory to knowledge portfolio of innovation driven firms (Hwang et al., 2019; Sharma & Biros, 2020). We posit that these firms create ideas for new products and their advancements using the knowledge of their employees. With an assumption that start up's performance and valuation is a function of their innovation, this study hypothesizes that the structure of information networks network, in terms of breadth and depth affects the firm's performance. Breadth refers to the scope of knowledge a firm has, and depth refers to the level of understanding a firm has in the domain area.

We argue that the characteristics of information network structure play an important role in generation of solutions in teams. Start-ups are good examples of such teams. Tech start-ups are usually a team of 11-50 employees focused on developing and capitalizing on a single technology or innovation, spearheaded by the founders and venture capitalists. With limited brand value, access to capital, and tangible assets, labor and intellectual property (IP) created by the said labor are critical resources for a start-up's inception, survival, and exit (IPO or acquisition). The personal investment of the founders in start-ups is more critical in these companies than rest of the employees. With firm size typically ranging from 11-50, these ventures are small enough to have a founder's influence covering all processes taking place in the company including research and development, operations, marketing, and sales. Prior research from UET notes that founders' heterogeneity in functional backgrounds, education, gender, and age are positively related to amount of capital raised (Zimmerman, 2008). Thus, due to their disproportionately large influence as innovation champions (Attewell 1992), we posit that the information network of small start-ups hinges on the knowledge stock of their founders.

Employees working for a firm have varying areas of expertise. The multitude of areas, or breadth of their knowledge, teams with diverse knowledge and backgrounds are known to have more creative output than ones with similar knowledge and background (Rietzschel et al., 2007). Past studies have found that having a wide range of knowledge helps individuals come up with new ideas. Individuals with broad knowledge need to be able to access that information and apply it to a different context to solve the problem. This idea hasn't been explored in relation to companies. In a startup, the breadth of knowledge is amplified as individuals with diverse skill sets can share knowledge to come up with an innovative solution. Thus, we posit:

Hypothesis 1: *Start-ups with high breadth of technical profile raise more capital.*

Similarly, Hwang et al. (2019) empirically demonstrated that individuals possessing a substantial depth of knowledge exhibit an enhanced capacity to generate superior ideas, thus surpassing their counterparts with shallower knowledge depths. However, this specific knowledge depth framework has not been extrapolated to the organizational context at the firm level. Employees working for a firm have varying degrees of expertise in many fields. The degree of expertise or, depth of their knowledge enables them to extract the underlying structure of the knowledge and the ignore the superficial attributes (Casakin, 2004). This makes them better problem solvers. In a team, their shared expertise is amplified as some team members with greater depth in an area may be able to come up with a more parsimonious and productive solution and hence, elevate the performance of the entire startup. Thus, we posit:

Hypothesis 2: *Start-ups with high depth of technical profile raise more capital.*

Revisiting the recombination uncertainty literature, use of novel components and combinations has led to more useful innovations in general, however, the variability in the recombination also results in breakthroughs and failures (Fleming, 2001). Fleming (2001) found that inventor's experimentation with new components and combinations leads to less success but increases the chances of breakthrough. As noted above, the presence of individuals possessing similar skills can have contrasting effects. On one hand, for a startup, having individuals with skill sets akin to those found in peer startups can yield advantages. This similarity can facilitate the exchange of ideas, harness the advantages of market trends, and enhance their capacity to attract investment. Conversely, this convergence of skills may also entail detrimental consequences, particularly in competitive markets. In such instances, heightened competition within a saturated market may impede the startup's ability to secure capital. Due to contradictory results from the literature about the combinations, we posit two competing hypotheses for the effect of diversity of technical profile on success of the firms.

Hypothesis 3a: *Start-ups with higher diversity in technological profile will raise more capital.*

Hypothesis 3b: *Start-ups with higher diversity in technological profile will raise less capital.*

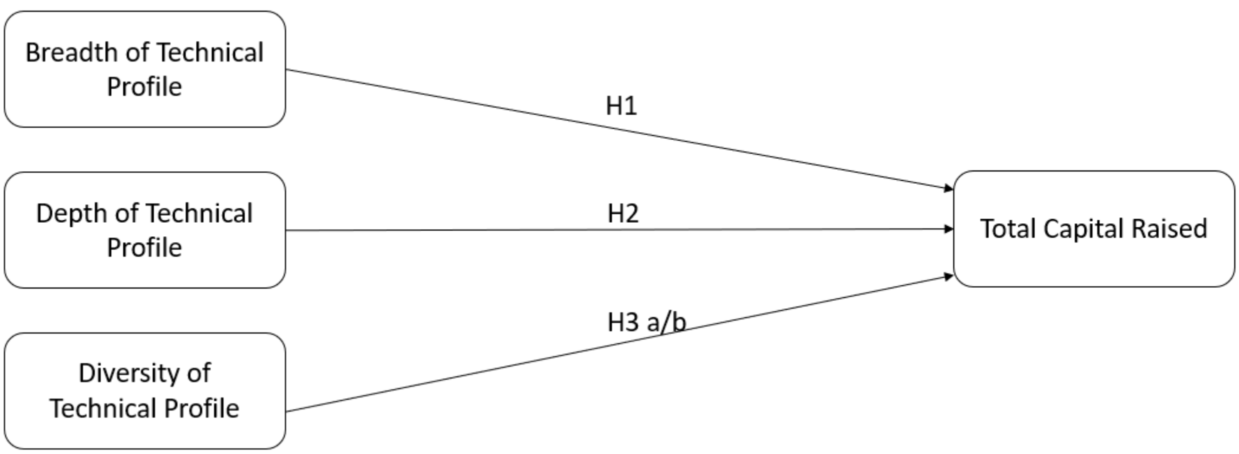

Figure 1. Model Tested

RESEARCH METHOD

For testing the above hypotheses illustrated in Figure 1, we select a competitive technical industry in start-up sphere: Internet of Things (IoT). IoT is an innovation driven IS artifact and constitutes wide array of disruptive products (Lowry et al., 2017), it is defined as 'connectivity of physical objects equipped with sensors and actuators to Internet via data communication technologies' (Oberländer et al., 2018). IoT encompasses a wide range of products including health and fitness monitoring devices, home security and automation, vehicular safety and automation, workplace productivity devices and even pet safety and surveillance. Though most IoT devices have common characteristics such as sensors, actuators and, underlying electronics, IoT is still an umbrella for a diverse portfolio of technologies ranging from health and fitness monitoring devices, home security and automation, vehicular safety and automation, workplace productivity devices and even pet safety and surveillance. A firm working on developing IoT devices needs employees of diverse backgrounds and skill sets and should endeavor to have a leader and workforce which reflects those needs.

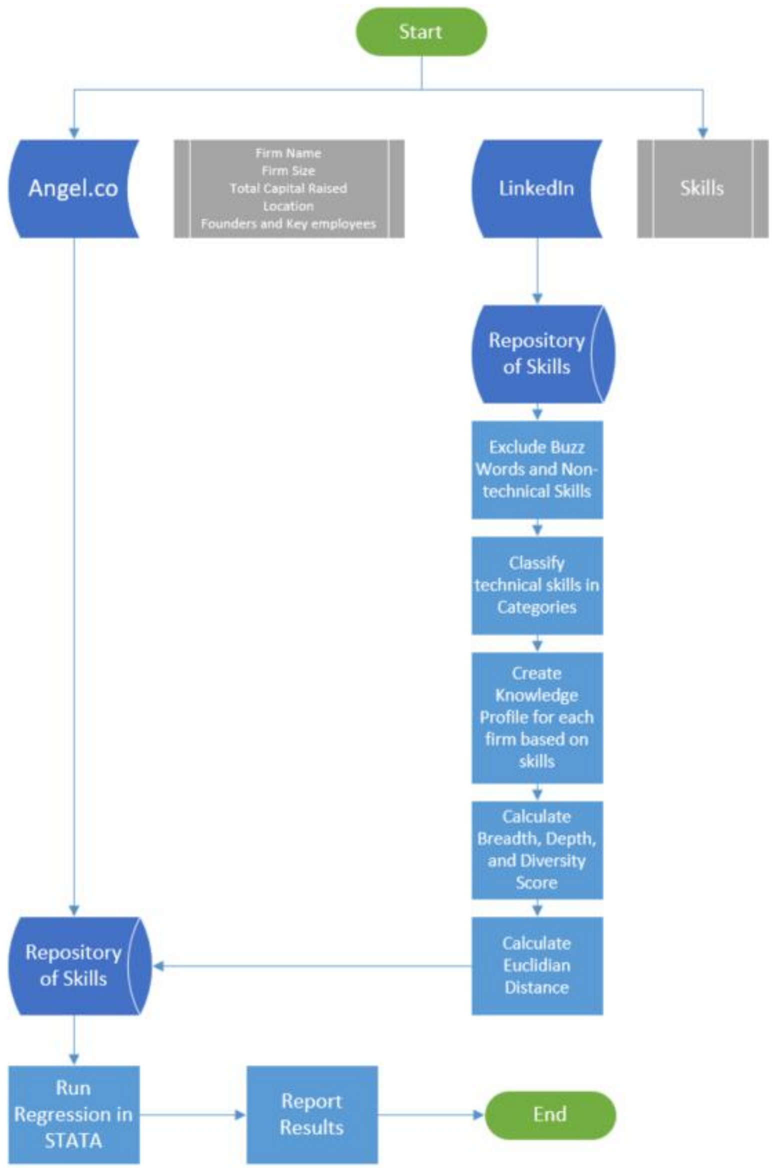

Figure 2: Activity diagram detailing research procedures

Data Collection

The firm and founder data were collected from AngelList and Linkedin respectively. The focus of our data collection was on IoT based start-ups located within the United States. Data collection occurred in two stages. First, the firm data was collected from Angel.co. AngelList provides self-reported data of the companies seeking further investments. We collected data from ten categories available including: company name, product, market, number of employees, physical location, website, date of establishment, current stage of funding, total funding raised, and founder skills which was limited to two founders or chief officers. The firm count was limited to 100 firms due to the flattening of the funding amount being received by the firms towards the bottom of the list. The companies listed after the first hundred were relatively new (not older than 2017) or generated insignificant investments.

The second stage was the recording of founder/chief officer skills from their LinkedIn profile pages. The profiles were accessed from LinkedIn links attached to the firms' Angel.co page. The skills data was collected for at least one and no more than two individuals explicitly listed as founders or chief officers of a firm. The mean size of the firms was 10-50 employees where two founders (or employees in senior leadership) were assumed to be reflective of a firm's desired employee skill set.

Skill sets were delimited from the comma separated raw data and the duplicate skills were removed generating 1361 unique skills from 180 employees. These skills were self-reported and contained technical skills, non-technical skills, and non-skills (buzz words added on Linkedin under skills). 1361 skills were then rated by two raters independently with 97 percent overlap in agreement with skills being rated 'R; for retain and 'NR' for not retain. Non-technical skills were not retained as they did not pertain to the scope of the study or were too general to classify into a unique, usable skill. These skills included buzzwords, managerial skills, leadership skills, interpersonal skills, and startup skills that elude quantification as tangible and measurable skills. The raters then rechecked both the N and R lists a second time. The rating process yielded 412 technical and 952 non-technical skills. We acknowledge that some skills may have general applicability across multiple categories used in the breadth measurement and believe the rating process yielded skills into the category that best fit their primary usage.

The 412 skills were classified into a table of 36 broader skill categories based on key areas. The 36 technical skill categories presented us with a more flexible and simplified measure of individual founder skills to compare the startup firms, their founder skill sets, and what individual skills or skillsets drive the success of tech startups. The categorization of skills revealed founders of 7 companies to have no technical skills listed on LinkedIn as such they were dropped from analysis.

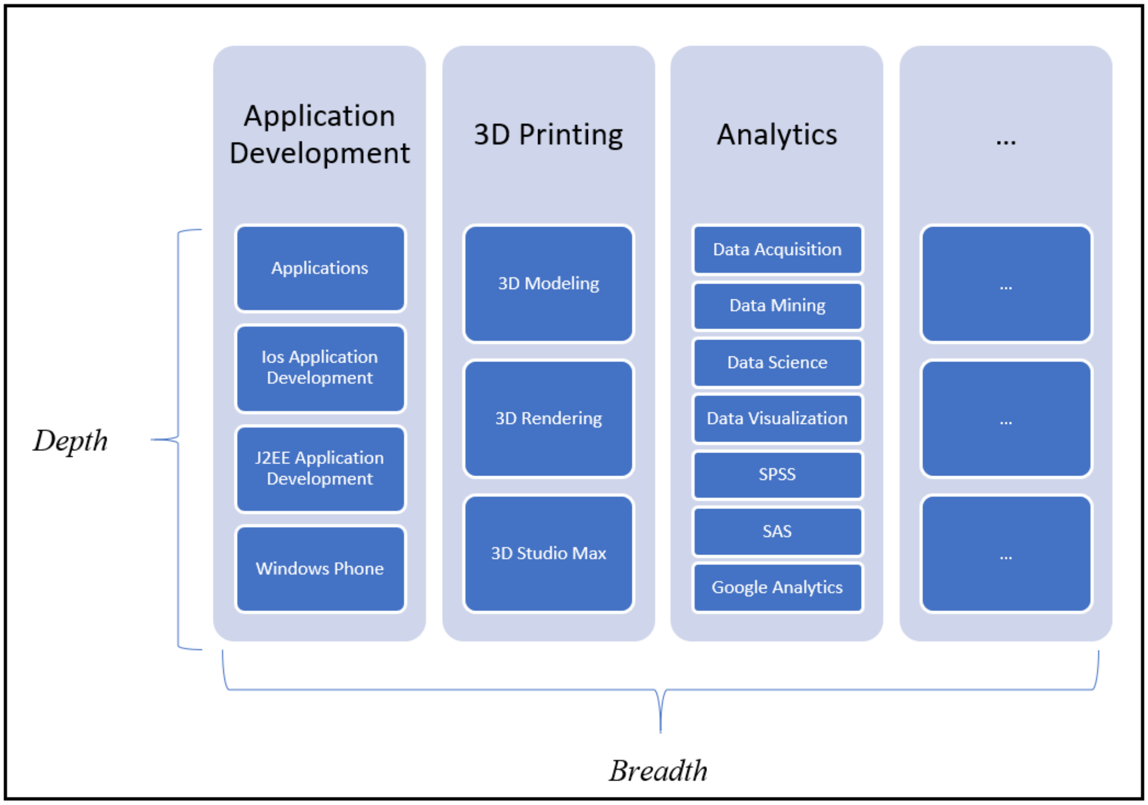

Figure 3: Measurement of Breadth and Depth of Information Network

Dependent Variable

Our dependent variable was "Total Capital Raised". Total capital raised is the value, the company has generated using venture capitalists. This value was reported on Angel.co for each firm. The capital raised by a firm is a representation of the confidence of venture capitalists regarding the chances of firm's growth. Firms with higher capital are more likely to get an IPO or a high-value acquisition. Due to high disparity in units of variables, the log of total raised was used. Table 1 shows summary statistics of all variables used in the model. This variable is often used as a proxy for firm's performance in extant research (Haw et al., 2000; Kim et al., 1993; Short et al., 2017).

Table 1: Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Total Capital Raised(TCR)	91	7472768	25200000	200000	230000000
Log(TCR)	91	14.53844	1.445174	12.20607	19.25359
Diversity of Profile	91	0.3064254	0.2219638	0.005423	0.6731507
Average Distance	91	2.67536	0.2855252	2.219951	3.365754
Depth of Profile	91	6.705946	11.90353	0.125	78
Breadth of Profile	91	6.142857	3.613467	1	14
Firm Size	91	44.83516	106.1379	10	1000

Independent Variables

The diversity of technical profile was calculated by using difference from the mean Euclidean distance of the firms in the data. 36 broad categories of skills as shown in figure 2, were used to make vectors for information networks of the firms. Thus, average Euclidean distance between firms indicates the average degree of difference between firms in the number of skills that they do and do not share. The deviation from the Euclidian distance of the firm shows if the is different from the average start-up, creating a baseline by which to compare technical profiles.. Thus, labelled diversity of profile.

The breadth of technical profile was calculated as the number of categories of skills in each technical profile. These categories were broad areas such as FinTech, App development, etc. and a representation of knowledge in diverse technical fields (As shown in figure 2).The depth of technical profile was calculated as the average number of skills listed in each category. Number of skills reported by individuals related to one category were pooled in the technological profile. This metric represents the level of area expertise of a founders' team and their confidence about their abilities in that area (As shown in figure 2). Firm size and average geographic distance from each other were used as control variables. Size of the firm is directly proportional to the funding for the venture. Firms in higher stages of finding tend to raise more capital. Thus, these controls explain a large part of the dependent variable.

Model:

$$LogRaised = \beta 0 + \beta 1 * KTMdistance + \beta 2 * AverageDistance + \beta 3 * Depth + \beta 4 * Breadth + \beta 5 * FirmSize + \varepsilon \qquad (1)$$

Here, LogRaised is the dependent variable denoting natural logarithm of the amount raised. KTMdistance represents the measure of diversity of technical profile. Depth and Breadth are independent variables representing depth and breadth of technical profile respectively. AverageDistance and FirmSize are control variables in this model. AverageDistance is represents average geographical distance between base of startups. FirmSize represents the size of the firm. β0 is the intercept, representing the constant or the baseline value of LogRaised when all independent variables are zero. β1, β4, β5 represent the coefficients for each independent variable, indicating the strength and direction of their impact on LogRaised.

RESULTS

We tested the relationships using a regression (1) in Stata. Our results indicated support for H2 and H3b. Depth of technical profile had a significant positive effect on total capital raised with a β coefficient of 0.0343. Diversity of a technical profile had a negative significant effect on total capital raised with β coefficient of -2.383. This shows that startups with high depth of knowledge in their profiles and the ones which are not similar to their peers in terms of technical profile have lower capital raised.

H3a which was a competing hypothesis and H1 did not find significant results. R-square for this test was 0.4693, showing 46.93% of explained variance for our dependent variable, total capital raised, within the hypothesized model. Comparing this model with a hierarchical model used in organizational research, a baseline model with just the controls (firm size and average distance) yielded an R-square of 0.2436. This indicates that our hypothesized relationships boost the explained variance by a delta of 0.2256. Figure 3 shows β values for each independent variable.

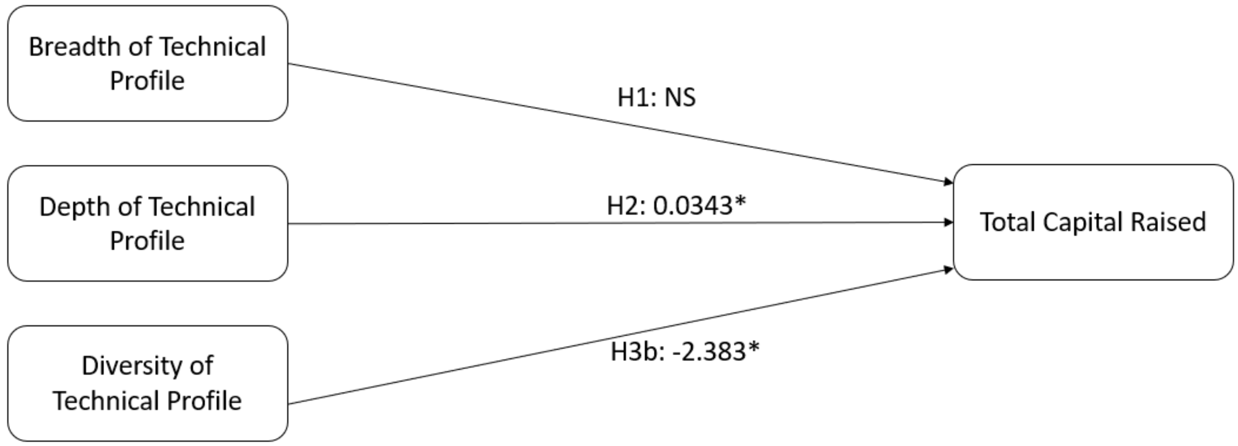

Figure 3. Results

Further, the diversity of technical profile leading to a negative coefficient encouraged us to hypothesize a curvilinear relationship between diversity of technical profile and firm performance. The basis for this hypothesis is rooted in our hunch that firms with technical profiles which deviate – that is to say they have more less overlap in their profile than other start-ups may not perform as well as they might due to competition, but firms with meaningful deviation from the ideal should have higher capital raised. Thus, we propose the following hypothesis.

Hypothesis 1c: *Diversity of technical profile has a U shape relationship with firm performance.*

Alternate Model:

$$LogRaised = \beta 0 + \beta 1 * KTMDISTSQ + \beta 2 * KTMdistance + \beta 3 * AverageDistance + \beta 4 * Depth + \beta 5 * Breadth + \beta 6 * FirmSize + \varepsilon \quad (2)$$

Here, most variables have same designations as the main model above. KTMDISTSQ stands for square of measure of diversity of technical profile.

Results of Alternate Model:

We tested this alternate model (2) in post-hoc analysis and found support for this curvilinear relationship. Our results indicated support for H2 and H3b. Depth of technical profile had a significant positive effect on total capital raised with a β coefficient of 0.026. Square of diversity of a technical profile had β coefficient of 14.663 showing that it has a U-shaped effect on total capital raised. The effect is negative up to a point showing that startups that are slightly different from peers in terms of their technical profile tend to generate less capital. After the inflection point, the high diversity score tends to have a positive effect on total capital raised. Figure 4 and 5 show the hypothesized relationship. The explained variance for this model was higher than our non-quadratic model at 49.32% while other relationships held.

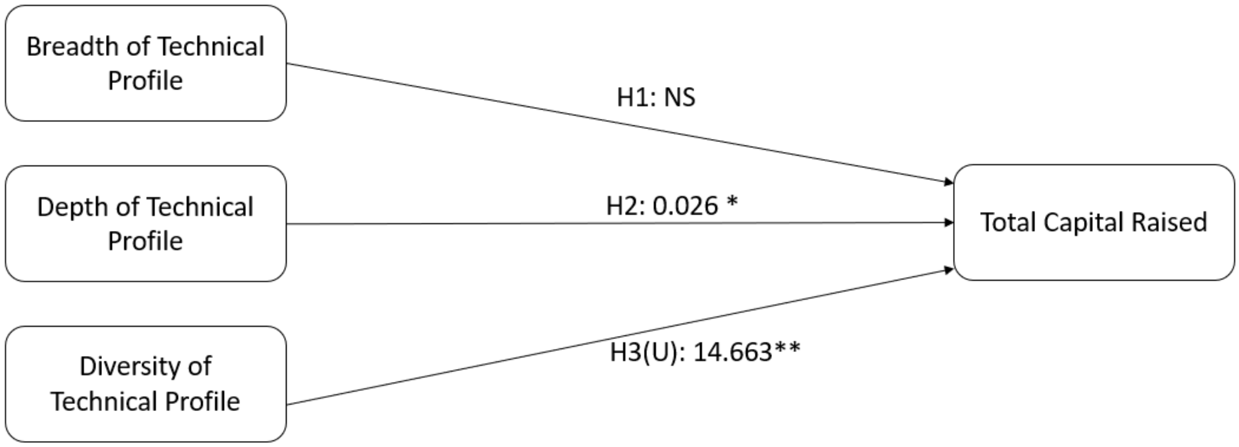

Figure 4. Results with model using proposed curvilinear relationship between total capital raised and diversity

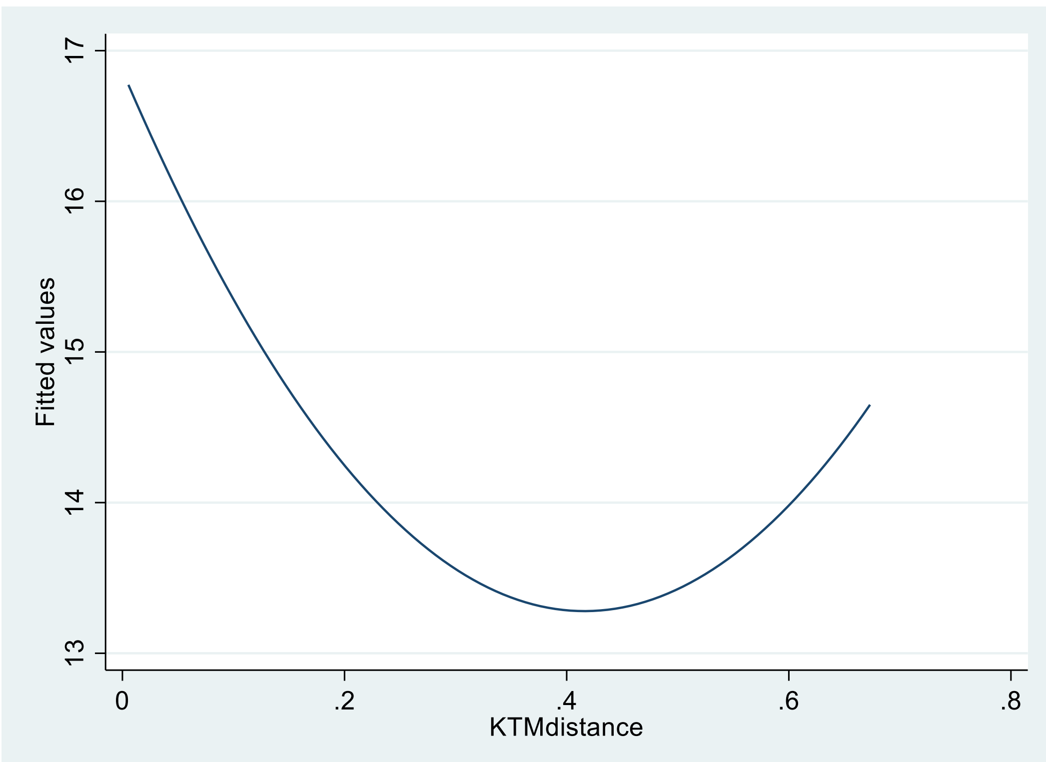

Figure 5. Curvilinear Relationship between diversity (KTMdistance) and total capital raised (Fitted values)

DISCUSSION

Our results show that aspects of technical profiles (diversity and depth) do affect firm performance. On testing our competing hypotheses about diversity of technical profiles, we found that firms with higher diversity in technical profiles in terms of skills of leaders have lower capital raised. This shows that firms should target hiring employees that are closer to peer firms. On post-hoc analyses, we also saw that there is a significant curvilinear relationship between diversity in technical profile and capital raised. This shows that diversity in technical profile built using skills of leaders may lead to the firm not being successful up to a point. After which, the deviation may be fruitful as our data shows that firms with significant difference are also successful. When establishing team members, if the firm is unable to stay well below the average diversity of expected profile of a start-up then, they should actively seek to extend that diversity to the extreme to increase success. The average KTMdistance reported was 0.306, a value that is close to the lowest points of the curve reported in figure 5. Start-ups should consider if they wish to aim for being less diverse or increasing their profile diversity greatly to increase success by "leaning into the curve".

Other reasons we think that may explain this relationship are; similar firms tend to compete with each other and hence, while some firms may lead, aggregate performance of these firms decreases as they deviate from the standards. However, significant difference in technical profile allows the firms to operate in the market with smaller competition leading to better ability to raise capital. We tested relationships between breadth and depth of technical profiles built using skills of founders on total capital raised. Analogical reasoning theory provides the foundation for these hypotheses. Our results indicate that depth of technology profile, i.e., more skills within the same area, has a significant effect on total capital raised. This shows that if the leaders of a firm have a higher specialization in select areas, they are considered more innovative and come up with products that catch investor attention more easily.

Breadth of technical profile on the other hand did not have a significant effect on total capital raised. This shows that firms with leaders who claim to specialize in many fields fail to attract adequate capital from investors. Firms hiring talent can use these findings by looking for talent that has higher specialization in one area instead of surface experience in many. Together these findings inform investment and hiring decisions in firms as well as research on the related topics.

LIMITATIONS AND FUTURE RESEARCH

While our research provides insights into many facets of organizations using technological skills of founders, this work is not without its limitations. We outline four main limitations in our current research and suggest future research to resolve them. First, due to resource constraints, our dataset is limited to 100 observations. We limited the sample size due to flattening of the funding amount received for firms after the first 100 listed on AngelList, and the relatively recent founding dates of those same firms had led to relatively insignificant funding compared to the firms included in our sample. While we tried to acquire a larger dataset, hand collecting public data is an intensive process as LinkedIn doesn't allow data scraping that would've streamlined data collection of firm leaders from their site. Future researchers can investigate programmatic solutions or data sharing deals with data sources listed in this paper. With a small dataset like this, results should be viewed in context as a pilot study. Second, we only used start-ups specializing in IoT for this study. To add more value to these results, future researchers must consider looking into other industries as well. Third, we acknowledge the limited amount of control variables used in the analysis and suggest future researchers investigate additional control variables. Last, we used self-reported skill data from LinkedIn. There is no uniformity in how skills are reported on LinkedIn and individuals may list skills in whatever order they chose and may choose to enumerate general technical skills or simply list the more general skill. Future researchers should consider investigating the relationship between the order of skills listed and outcome variables such as capital raised.

CONCLUSION

The outcomes of this study offer valuable insights into the role of founders' technical skills in the fundraising capabilities of start-ups. A deeper technical profile, suggesting a comprehensive mastery or specialization in certain areas, appears to be beneficial in attracting more capital. Conversely, start-ups with a more diverse technical profile, deviating from the norm, may face challenges in their fundraising efforts. It is possible that potential investors perceive such non-standard skillsets as a risk or mismatch for the targeted market or product. However, it is worth noting that the breadth of the technical skills, or the range of different skills, did not play a discernible role in the capital raised. Start-ups and their founders may benefit from this understanding by strategically presenting their skills and expertise to align more closely with investor expectations and market demands. Future studies may further explore the underlying reasons for these findings and assess the potential long-term impacts of these technical profiles on start-up success.

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