ARE WELL-CONNECTED ENTREPRENEURS MORE SUCCESSFUL? A STUDY OF START-UP FOUNDER LINKEDIN PROFILES AND THEIR ROLE IN INVESTOR DECISION MAKING

by

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ABSTRACT

Author: Banerji, Devika. PhD
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Title: Are Well-Connected Entrepreneurs More Successful? A Study of Start-up Founder LinkedIn Profiles and Their Role in Investor Decision-Making
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Social capital through connections in networks has been argued to be important for startup enterprises. Founder human capital qualities like education, experience, skills have also been shown to be important predictors of startup success. However, does founder social capital matter for startup success beyond founder human capital? To answer this question, this project draws from the decision-making literature and uses five decision strategies to explore how founder human capital and social capital are associated with investment funds raised by startup companies.

Two studies were conducted. The first study investigated if a decision strategy that looks at founder social capital better predicts which company raises more investment funds than a decision strategy that only uses founder human capital. The second study investigated if actual investors and entrepreneurs, of varying expertise levels, integrate founder social capital variables while making investment decisions.

Both studies found that number of LinkedIn connections of founders of a company was the best predictor of investment funds raised by the company. The first study showed that decision strategies that use social capital cues are similar in predicting successful companies compared to strategies that use human capital cues. The next study showed that, contrary to our expectations, decision strategies that use social capital cues better predict investor choices than strategies that use only human capital cues. It was expected that models that used human capital cues would be better predictors of investor choice behavior than social capital cues. Therefore, the two studies show that founder social capital is associated with investment funds raised by a startup company and investors do take founder social capital into consideration while deciding which startup company to invest in. In doing so, the studies establish the importance of founder social capital in the entrepreneurial context.

Keywords: Entrepreneurship, Social Capital, LinkedIn, Investor Decision-Making

"It's not what you know, it's who you know."

LinkedIn, 2018

INTRODUCTION

The popular phrase, "It is not what you know, it is who you know," encapsulates the often-iterated rhetoric that our personal connections or social networks are more valuable for our professional growth than our capabilities and skills. One such context where this phrase and its impact is strongly felt is the entrepreneurial context. Social connections in networks have been argued, for over 30 years, to be important for startup enterprises (see Aldrich & Zimmer, 1986; Dubini & Aldrich, 1991).

The startup industry is full of popular anecdotes that underline the importance of entrepreneurial networking that can potentially lead them to investors who see promise in a founder's early-stage venture. One such story is that of entrepreneur Sean Parker, a college drop-out, who networked his way up as a teenager to start various startups before joining Facebook as President in its early stages. Arguably, Parker had low human capital as he did not have a college education and had amassed only a few years of professional experience. However, he is credited with bringing to Facebook what it originally lacked, a valuable social network (Hill, 2013). Sean Parker's connections led investor Peter Thiel to become one of the first big investors in Facebook that would then grow to become the world's largest social media network (Hill, 2013). The social connections of Sean Parker were key for the success of the new startup company.

This dissertation aims to contribute to our understanding of the role of social connectedness in the success of startups by taking a decision-making perspective and by asking three basic, related questions. All three questions try to understand if founder social capital cues are important to consider beyond founder human capital cues when making investment decisions. Whereas the first question takes a prescriptive perspective, the second and third question are descriptive.

(1) Prescriptive question: *Does a decision strategy that looks at social capital better predict startup investment funds than a strategy that ignores social capital cues and only looks at human capital cues?*

Prescriptive studies focus on our understanding of which decision strategies yield the best decisions and how deciders should form their decisions, while descriptive studies describe how actual deciders form their decisions (Bell, Raiffa, Tversky, 1995; Hoffrage & Reimer, 2004).

The second and third questions are descriptive and ask if actual deciders use social capital cues when making investment decisions and whether this holds for various involved groups of deciders.

(2) General descriptive question: *Do investors use decision strategies that integrate founder social capital while making investment decisions?*

(3) Group-specific descriptive question: *Do investors systematically differ in their decisions from entrepreneurs and are there systematic differences between experts and novices*?

The literature on entrepreneurship provides some empirical evidence that human and social capital cues are related to the success of companies and are considered in investment decisions. Both, human and social capital have been shown to be important for entrepreneurial enterprises. Several studies have demonstrated that founder *human* capital indicators like education levels, previous experience, and skills are associated with the ability of a new venture to survive and succeed (see Cooper, Gimeno-Gascon, & Woo, 1994; Unger, Rausch, Frese, & Rosenbusch 2011;). A separate line of study has shown that founder *social capital* indicators like founder network size, group memberships, and marital status are associated with new venture success (see

Bruderl & Prisendorfer, 1999; Nann, Krauss, Schober, Gloor, Fischbach, Führes, 2002). There is very limited evidence, though, as to whether it is worthwhile to consider social capital cues beyond human capital cues when predicting which startup company will be more successful in raising investment funds. This dissertation aims to fill this gap by drawing on the decision-making literature. Specifically, the dissertation introduces five decision-strategies that differ in the utilization of founder social capital and human capital cues.

The dissertation proposes a lexicographic investment-decision model that considers both human capital cues and social capital cues, in a step-wise manner, to predict startup success. This strategy is compared with other alternative decision strategies that integrate founder human and social capital, in varying ways, to predict startup investment funds. This basic premise is studied in two parts using two different decision-making perspectives – prescriptive and descriptive.

The first part of the dissertation focuses on a prescriptive perspective by addressing the first research question. Specifically, a prescriptive study is described that investigates if the proposed lexicographic investment decision-model using founder human and social capital yields better results in predicting startup investment funds than alternative decision models.

The second part of the dissertation addresses the second and third research questions by asking if the decision model is also descriptive. To this end, a second study is described that explores if potential investors pay attention and consider social capital cues beyond human capital cues when making investment decisions. The study compares different groups of involved agents as the literature on decision making suggests that experts and novices differ in their levels of accuracy (Holstein, 1972; Shanteau 1992), the amount and kind of information they use (Andersson, 2004; Retamero & Dhami, 2009), and the patterns in which they access and process available information (Jacoby, Jaccard, Kuss, Troutman, & Mazursky, 1987). The dissertation concludes with the results of the second study, a discussion, and an agenda for future research.

PART I: THE PRESCRIPTIVE APPROACH

CHAPTER 1: RELATIONSHIPS OF HUMAN AND SOCIAL CAPITAL WITH ORGANIZATIONAL SUCCESS AND STARTUP OUTCOMES

The first part of this dissertation takes a prescriptive approach and studies the startup environment to answer the question to what extent founder social and human capital explain startup success outcomes.

Human capital refers to cumulative knowledge, capability and skills that people or organizations possess (Glaeser, Laibson, & Sacerdote, 2002). Social capital has been defined as resources that are available to individuals and organizations through their interpersonal connections (Luthans et al., 2004). From a decision-making perspective, it is key to understand if it is worthwhile to look at social-capital cues when making investment decisions. Some existing research, within the entrepreneurial context, has explored correlations of founder human and social capital with the success of startup companies. In the following three sections, research is summarized that looked at relationships of human-capital variables and social-capital variables with some measure of objective outcomes and startup success.

1.1. Human Capital and Organizational Outcomes

Several studies have found a positive relationship between founder human capital variables and entrepreneurial success. For example, in a meta-analysis consisting of 70 independent samples, Unger, Rausch, Frese and Rosenbusch (2011) concluded that human capital indicators have a significant but small correlation (r=.10) with startup success. This finding is echoed by other researchers who have found association between founder human capital indicators and various startup outcomes. For example, Cooper, Gimeno-Gascon and Woo (1994) did a questionnaire-based analysis of 1,053 new ventures and found that human capital of founders (measured by education and race) predicted both startup growth and survival.

How can these studies inform decision making? These studies suggest that it is worthwhile to consider a very simple decision strategy as a potential candidate for a prescriptive model of investment-decision making, the *Human-Capital Strategy*: If you have a choice between two entrepreneurs, invest in the entrepreneur who has higher human capital.

1.2. Social Capital and Organizational Outcomes

There are also some studies indicating that founder social capital contributes to new venture success and sustenance. For example, Bruderl and Prisendorfer (1999) surveyed 1,700 business owners in Germany about their network connections and compared their responses with startup success variables like survival, employment, and sales growth. They found positive relationships between the level of network support business owners reported and venture success variables. Similarly, Bosma, Praag, Thurik, and DeWit (2004) surveyed over 1,000 entrepreneurs and concluded that founder social capital predicted the profitability of a new venture. Social capital was operationalized as contact with other entrepreneurs, information gathering from networks, and the degree of emotional support from spouse. Taken together, this research provides indicates that social capital is important to new venture emergence, profitability, knowledge acquisition, sales and survival.

The studies on social capital suggest that it is worthwhile to consider a second, simple decision strategy as a potential candidate for a prescriptive model of investment-decision making, the *Social-Capital Strategy*: If you have a choice between two entrepreneurs, invest in the entrepreneur who has higher social capital.

1.3. Human Capital and Social Capital Cues

Might it be worthwhile to consider social-capital cues beyond human-capital cues when making an investment decision? There are only very few empirical studies that have looked at human and social capital cues simultaneously and explored their correlation with organizational success or other organizational outcome variables.

The answer to this question depends in part on whether and to what extent human capital and social capital cues are correlated (Rieskamp & Reimer, 2007). If both variables are highly correlated in that entrepreneurs with excellent education and expertise are also those entrepreneurs who have better social connections, it should not matter much whether the investment decision is based on human or social capital cues. Indeed, there is some empirical evidence to show that human and social capital tend to be correlated with each other. Glaesar, Laibson and Sacerdote (2002) theorized that human and social capital are positively correlated because individuals who invest in their human capital (education, skills, knowledge acquisition) tend to have more social capital (extensive social networks). Such a positive association was also found by Florin, Lubatkin and Schulze (2003) who showed that organizational human capital was positively correlated with organizational social capital (r=.46). Florin et al. (2003) explain the correlation as a virtuous cycle where organizations with larger social network (high social capital), find more competent workforce (high human capital), which in turn leads to larger and richer networks (high social capital) which again leads to better human capital. While the correlation is not perfect, a positive association between human and social capital can reduce the need to look at both human and social capital to predict organizational outcomes. Therefore, this makes the case for decision models that look at either human or social capital.

These studies may suggest that it is sufficient to look at either human or social capital cues when making investment decisions as those two classes of cues are positively correlated. However, there is also evidence to suggest that it may be wise to look at both types of cues when forming decisions. Firstly, the reported studies mainly come from research on organizational outcomes and do not focus on entrepreneurial or early-stage companies. Secondly, there are only very few studies and the reported correlations are only relatively weak. Thirdly, there are also empirical studies that suggest additive or interaction effects of human and social capital cues. For example, Florin, Lubatkin and Schulz (2003) observed that social capital moderated effect of human capital on organizational outcomes. Florin et al. (2003) found that while an organization's human capital was positively associated with sales, it was negatively associated with sales growth and had no impact on return on sales. However, when social capital was added to their model, human capital had a positive association with return on sales and sales growth. Based on this evidence, Florin et al. (2003) concluded that social capital leverages the productivity of human capital for an organization. Honig (1998) also provided evidence that social capital adds to the effects of human capital on organizational outcomes. He studied the performance of 215 finance microenterprises in Jamaica and found that owners who were frequent church goers and were married, and arguably had higher social capital, had higher profitability than those owners who just had high human capital in the form of high education levels.

Based on these latter findings, one might expect that decision strategies that take both human as well as social capital cues into account will be better suited as investment strategies than strategies that are restricted to one class of cues by utilizing only human or social capital cues. In the next chapter, three decision strategies are described that consider both dimensions. Specifically, a frugal lexicographic model is offered that is sequential. The model considers human capital first. In cases in which two companies are not sufficiently distinct in their human capital resources, the model utilizes social capital cues.

CHAPTER 2: THE LEXICOGRAPHIC HUMAN/SOCIAL STRATEGY: A MODEL TO CHOOSE BETWEEN TWO STARTUP-COMPANIES WHEN MAKING INVESTMENT DECISIONS

There are many potentially viable strategies that can be used by a decider in a situation in which a decider has to choose among two or more alternatives that take two cues into account (see Payne, Bettman, & Johnson, 1986; Rieskamp & Hoffrage, 1999; Reimer & Hoffrage, 2006).

One decision strategy that can be used to make investment decision based on human and social capital cues is the *Unit Weight Linear Model* (UWM). *UWM* can be used as a baseline for models that take both founder human and social capital into consideration to predict startup success. The *Unit Weight Model*, which is also known as the Dawes Rule (Broder, 2002; Gigerenzer, Czerlinski, & Martignon, 1999), assigns binary values (0 and 1) to all cues available in the environment. For example, if a founder has high human capital, the strategy assigns a binary value of 1 to the cue, while a founder with low human capital is assigned a value of 0. Similarly, a founder with high social capital is assigned a value of 1, while a founder with low social capital is assigned a value of 0. The cue values are then summed up and the alternative with the higher overall value is selected. Based on this procedure, founders are assigned one of three logically possible sum scores: A founder with high human and social capital will received a sum value of 2; a founder with high human capital and low social capital (or vice versa) will have a value of 1; and a founder with low human and social capital will have a value of 0. To predict which company will be more successful in raising investment funds, the strategy chooses the alternative that has the highest sum score.

An alternative model, which this project proposes, is the *Lexicographic Human/Social Capital Strategy* (Figure 3.1).

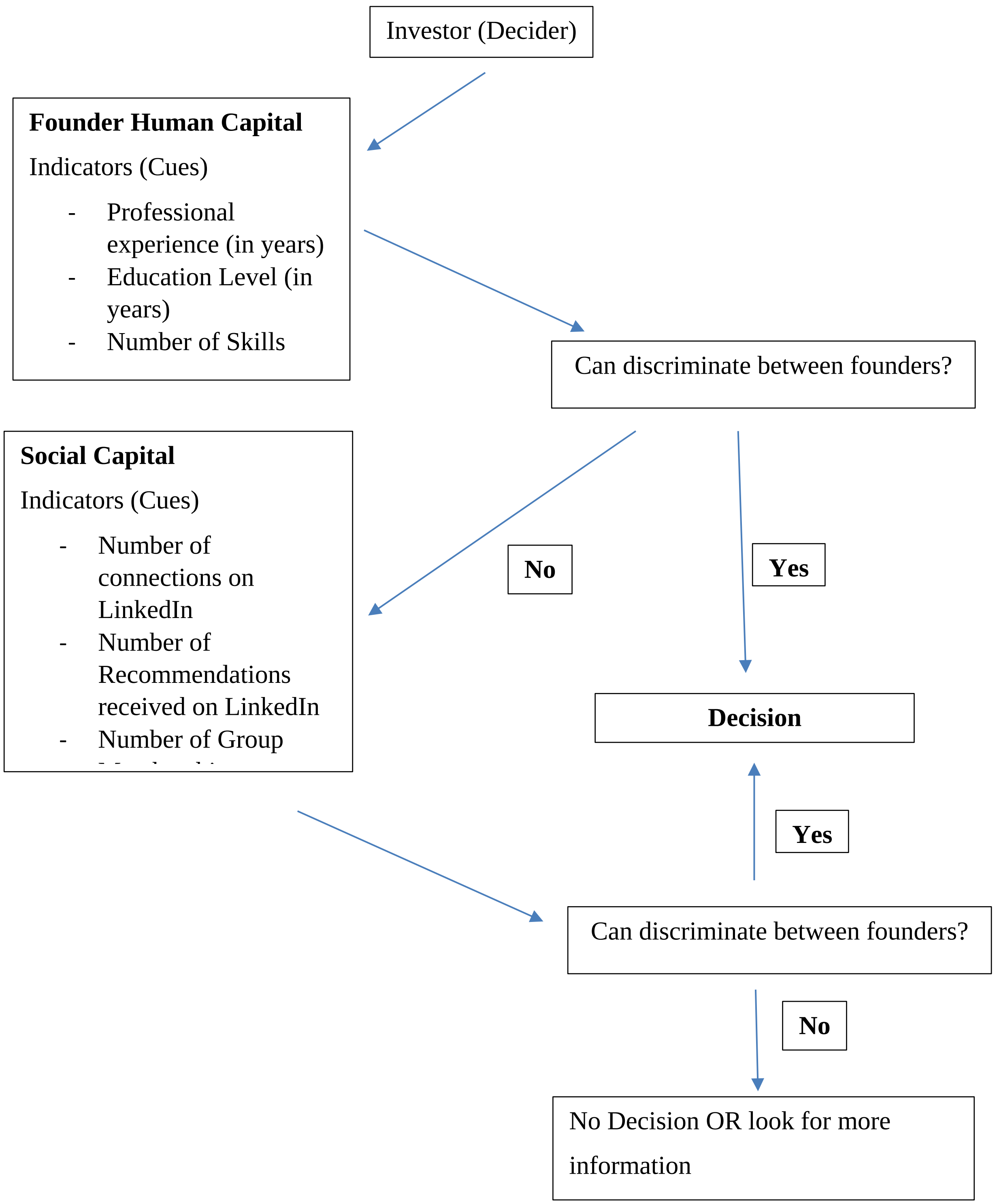

Figure 1 Two-step lexicographic human/social capital decision strategy

The model can be used to predict startup success using both founder human and social capital. It is a two-step lexicographic strategy. A lexicographic strategy proposes a sequential information search pattern. Lexicographic models have step-wise rules that define when a decider compares all the attributes and when additional information is ignored. According to this strategy, to predict which startup company will be more successful based on how much investment funds a company raises, the model, in a first step, accesses founder human capital of the companies. If there is a difference in the founder human capital of the alternatives, that is, one company has a founder with more human capital than another, the strategy predicts that the founder with more human capital will raise more investment funds. In this case, the model stops information search and does not access founder social capital. However, in the case that both companies have founders with high human capital or low human capital, the model is unable to predict which company will raise more funds. Therefore, in this case, the model, in a second step considers founder social capital levels and predicts the company with the founder with higher social capital will raise more investment funds. Lexicographic models have been shown to have high predictive validity in various contexts, including consumer choices (see Diekman, Dippold, & Dietrich, 2009) and group decisions (Reimer & Hoffrage, 2006; Reimer & Katsikopoulos, 2004).

As a last strategy, an alternative lexicographic model is considered that is very similar to the *Lexicographic Human/Social Capital Strategy* but considers cues in a different order. The *Lexicographic Social/Human Capital Strategy* differs from the *Lexicographic Human/Social Capital Strategy* by focusing on social capital cues first. This model reverses the order of human capital and social capital cues. To predict which company raises more investment funds, in a first step, the model looks at the social capital level of the founders.

If the alternatives differ in their founder social capital, the strategy stops information search and chooses the company with the founder who has the higher social capital; information about founder human capital is deliberately ignored. However, if two companies have founders with similar levels of social capital, the model, in a second step, accesses information about founder human capital and predicts the founder with higher human capital will raise more investment funds.

The three decision-models consider both founder human and social capital when making decisions. Information box given in Table 3.1 on the next page provides an overview of the five introduced strategies including the human capital and social capital strategies introduced in Chapter 2. The strategies differ in whether they consider only one cue or process cues in a sequential order. The four frugal decision-making strategies are compared with the *Unit Weight Linear Model* that always utilizes human as well as social capital cues, as a baseline.

Table 1 Information table explaining the five decision-strategies used in this study

Decision Strategy	***Description***
Human Capital Strategy	A simple decision-strategy, which to predict startup success, only looks at founder human capital and ignores founder social capital. Therefore, between given alternatives, this strategy predicts the company with the founder who has higher human capital to be more successful.
Social Capital Strategy	A simple decision-strategy, which to predict startup success, only looks at founder social capital and ignores founder human capital. Therefore, between given alternatives, this strategy predicts the company with the founder who has higher social capital to be more successful.
Unit Weight Linear Model	Looks at both founder human capital and social capital to predict startup success. The strategy weights attributes using binary values (0 and 1). Between given alternatives, the strategy predicts the alternative with the higher additive sum of both attributes (founder human and social capital) to be more successful.
Lexicographic Human/Social Capital Strategy	Founder human capital and social capital is accessed in a sequential manner to predict startup success. First, founder human capital is compared for given alternatives and the founder with the higher human capital is predicted to be more successful. Founder social capital, in this case is ignored. If, companies have founders who have similar levels of human capital, the strategy then compares founder social capital and predicts the company with the founder who has higher social capital to be more successful.
Lexicographic Social/Human Capital Strategy	Reverses the order in which founder human capital and social capital is accessed. In this model, founder social capital is accessed first and the company with the founder who has higher social capital is predicted to be more successful. In this case, information about founder human capital is not accessed. In the case, that companies have founders with similar levels of social capital, the strategy then accesses information about founder human capital. In this step, the company with the founder with higher human capital is predicted to be more successful.

CHAPTER 3: LINKEDIN: IDENTIFYING HUMAN CAPITAL AND SOCIAL CAPITAL CUES

The design of this project is inspired by the theoretical and methodological framework developed by Egon Brunswick (1957). Brunswick argued that to understand the cognitive processes of an individual, a researcher needs to understand how a person uses cues available in the environment, that are imperfect indicators of a criterion, to predict the criterion. In the context of investor decision making, future startup outcomes act as the distal criterion. A distal criterion is not directly observable; therefore, an individual infers it using proximal cues (Brunswick, 1957; Reimer, Hertwig & Sipek, 2012). Proximal cues within the context of startup success could be founder experience, founder connections, a founder's geographic location, mutual connections, endorsements or references and a plethora of financial indicators that can be measured and used to make predictions about the future success of a startup company. An investor can make inferences about the potential of a company to succeed based on various cues available. One potential source where investors can access both founder human and social capital cues is professional social media networking site LinkedIn.com.

The availability of data on LinkedIn provides the opportunity to fill gaps within the entrepreneurial research. Several researchers have tried to establish the importance of network connections of founders for success of startup companies. Most studies have struggled to establish a direct connection between number of connections of founders and tangible financial outcomes or investor behavior (see Burt, 2000; Daviddsson & Honig, 2003; and McEvily & Zaheer, 1999). Some studies that stand out are studies conducted by Light (1984), Bates (1997) and Zimmer and Aldrich (1987). Light (1984) conducted interviews to show that ethnic minorities tend to raise more capital through their interpersonal connections. Bates (1997) interviewed 2,000 Chinesse and

Korean firms to show that interpersonal connections were crucial for firms to raise funds. Zimmer and Aldrich (1987) interviewed 580 entrepreneurs to show that family connections and friends was perceived to be important for entrepreneurs to sustain their ventures. While these studies do provide some evidence of the beneficial impact of social networks on financial resources of startup firms, they rely solely on interviews, case studies and survey questionnaires as methods of data collection. These data collection methods, while insightful, are self- reported, lack cue-specific information, and have been shown to be limited in its scope and accuracy (Hoang & Antoncic, 2003; also see Banerji & Reimer, 2019). There is also extremely limited research that has explored the importance of social networks in investor decision-making. A notable exception is Shane and Cable (2002) who conducted 50 interviews of investors to show that investors tend to invest in founders who are well-known or are able to garner endorsements from people who are connected to the investors.

Part of the reason why the direct connection between founders' social networks, financial outcomes and investor choice behavior remain underexplored has been the absence of data sources that could provide information about founder networks. Such an absence of information sources has made empirical exploration network-outcome and network-investor behavior a challenge. The challenge is two-fold. First, the lack of network information that is more exhaustive and accurate than individual self –reports. Second, an information source that is available in the environment that can be used to study how investors can assess and respond to social capital cues of founders.

One way that investors can draw cues about a founder's social capital is through LinkedIn.com. LinkedIn provides an avenue through which founders and investors can communicate about their professional connections and other indicators of both social and human capital. This project capitalizes the information about founder connections available on LinkedIn.

This is in line with research that has argued that cyber resources have enabled new processes of "interactions and interconnections among individual documents, data, analytic tools and concepts" (Huang, Contractor & Yao, 2008, p.28). Online communities like LinkedIn are large knowledge networks that contain multi-dimensional information which can be used to study networks and their role in different organizational contexts (Huang et al., 2008).

Targeted at professionals to connect with other professionals and create a human resource network, LinkedIn's profile, unlike that of other social media networking sites like Facebook and Twitter, acts like an online resume. LinkedIn provides information about a user's professional and educational background. Also, being a social networking site, LinkedIn also provided network cues that can be used to infer information about a founder's network.

The role of LinkedIn or the founder and human capital cues that it contains has not been explored by researchers within the entrepreneurial context. Within the financial context, Vismara (2016) explored how investors gather information about companies in crowdfunded campaigns and showed that investors who have LinkedIn profiles tend to invest more than the average investor and influence other investors into investing in their choice of companies. Also, there is emerging evidence that online social networks are associated with funds raised in certain entrepreneurial contexts like crowdfunded enterprises. Various studies that have explored crowdfunded sites have shown that online connections of founders is associated with funds raised by founders on crowdfunded internet sites (see Bellefamme, Lambert & Schwienbacher, 2013; also Mollick, 2014). Thus, LinkedIn has been shown to be a data source for other related organizational contexts, while its relevance and use within the entrepreneurial and investment-decision-making contexts remains underexplored.

Founder human and social capital cues can be operationalized through LinkedIn in several ways. Human capital and social capital are constructs that cannot be directly measured (Grootaert & Baestelaar, 2001) but are inferred through cues. LinkedIn offers both, human and social capital cues of founders, which can act as indicators for founder human and social capital.

Previous research has measured founder human and social capital in various ways. Drawing from existing studies, the current studies measures human capital using three cues available on LinkedIn: 1) education level of the founder in years; 2) work experience of the founder in years; and 3) total number of skills reported by founder. This is consistent with studies within the entrepreneurial context that have looked into the impact of human capital on startup outcomes. Studies have measured founder or organization human capital as education levels (see Gimeno et al., 1994; Sandberg & Hofer, 1987), work experience in years (see Cooper & Bruno, 1977), and number of skills a founder reported to have or managerial know how (Gimeno et al., 1994). Unger et al. (2011) in their meta-analysis of human capital variables and startup performance concluded that human capital variables like “knowledge and skills” or “task relevant experience” were the best predictors of startup performance as opposed to variables like “education or schooling.” This is reflected in the information available on LinkedIn. Founders report the companies and the duration they have been active professionally, they report their education levels, and they list their skills.

Founder social capital is also measured through three cues available on LinkedIn. These are: 1) the number of connections that a founder has on LinkedIn (or the network size), 2) the number of groups the founder is a part of on LinkedIn (group membership), and 3) the total number of endorsements a founder received on LinkedIn (endorsements). There is more variation in the ways researchers have measured social capital than how human capital has been measured.

However, the cues found on LinkedIn are consistent with the various ways in which researchers have theorized and measured founder and organizational social capital. For example, a recurring measure of social capital in existing research has been network size (see Baron and Markman, 2000; Shane and Cable, 2002). Shane and Cable (2002) also used endorsements or referrals as a measure for social capital. Furthermore, some researchers have operationalized group memberships as a measure of social capital (see Davidsson & Honig, 2003).

The advantage that LinkedIn provides is that the social capital indicators communicated through the medium are part of the startup environment. The medium contains social and human capital indicators of founders as it is communicated to a public domain and is available to an investor. Therefore, LinkedIn replicates the environment and the information available in the environment about social and human capital cues of a founder in a more ecologically valid way than self-reported social capital and network data. However, using LinkedIn as a data source for social capital does have limitations. The site does not communicate about the network position, the level of trust that a member has in his/her connections, and the level of support people receive from their networks. These are some of the measures often used by researchers. These measures allow investors to make inferences about the value of a person's social network and support by looking at network size, endorsements and group memberships that are available on LinkedIn. Furthermore, while there is limited understanding of how well LinkedIn represents the social networks of a person, however, researchers in other organizational contexts like corporate recruitment have shown that LinkedIn is an useful tool for decision-makers and the information on LinkedIn is reliable. Caers and Catelyns (2011) showed that within the context of organizational hiring, recruiting professionals access information on LinkedIn about potential applicants. The study showed that 70% of recruiters rely on the site to decide which applicants should be interviewed. Guillory and Hancock (2012) also demonstrated that people are less likely to be deceitful on their LinkedIn profiles, particularly about their previous experience and educational background.

In summary, while there are limitations associated with using information from a social media networking site, there is evidence to show that LinkedIn can potentially be a valid source of social and human capital cues of founder so startup ventures. This project builds on the opportunity that LinkedIn provides to test whether founder social capital can explain startup success beyond measures of human capital.

CHAPTER 4: STUDY 1

[1]The goal of this dissertation is to contribute to our understanding of the role of social connectedness in the success of startups by taking a decision-making perspective. The first research question asks if social capital cues are important to consider beyond human capital cues when making investment decisions.

1) Prescriptive question: *Does a decision strategy that looks at social capital better predict startup investment funds than a strategy that ignores social capital cues and only looks at human capital cues?*

To answer this question, this project tests a *Lexicographic Human/Social Capital Strategy* (see Figure 3.1) that looks at both founder human and social capital variables in a sequential manner to predict startup success. The model is compared with 4 other viable decision strategies (see Table 3.1). The study sample, measures and the procedure are elaborated upon in the next sections.

4.1. Sample and Procedure

There are two units of analyses for this study. The first unit refers to the startup companies, and the second unit refers to the founders of the companies. In a first step, data about companies were downloaded from crowdsourced startup database Crunchbase.com. Crunchbase.com is an online crowdsourced database of startups, founders, venture capitalists and other allied funding agencies. The entire company database of Crunchbase.com was downloaded after accessing

[1] While this dissertation was in progress, a paper based on the first study of this dissertation was accepted and made available online in a peer –reviewed journal. The article will be available in print in 2019 - Banerji, D., & Reimer, T. (2019). Startup founders and their LinkedIn connections: Are well-connected entrepreneurs more successful?. *Computers in Human Behavior,90*, 46-52.

permission from the website administrators. The initial data file had the name of all the companies in the database, the years they had been in operation, to which category they belong (operating, acquired, or IPO), the number of rounds of funding they had received, and the amount of funds they had raised.

In a second step, the companies that were located in the United States and were operating in the information and technology industry were selected. This was done to standardize geographic, cultural and industry factors that might impact funding of companies. This yielded 3,636 companies of which 3,060 were operating companies, 521 companies were acquired, and 55 companies were IPOs. In a third step, 50 companies from each of the three categories were randomly selected that were then used for further analyses.

For each of the 150 randomly selected companies, information from Crunchbase.com about the founders of the respective companies was collected. It turned out that Crunchbase.com did not have complete information for all the randomly selected companies, particularly for the companies that have gone to IPO. Therefore, more companies were randomly selected from the original database until we had 50 companies in each of the categories that had complete information. We found 50 companies with complete information for operating and acquired companies respectively. However, as there were only 55 companies with IPO status total, we could only collect complete founder information for 29 IPO companies.

Some of the companies had single founders while others had multiple founders. This procedure yielded 129 companies that had a total of 227 founders. After the name of the founders were collected, the public LinkedIn profile of each founder was accessed, and data was recorded about their level of education (in years), years of professional experience (in years), number of skills reported by the founder (skills), the number of connections of each founder (network size), number of recommendations the founder has received (endorsements), and the number of groups a founder was a part of (group membership).

4.2. Measures

*Social Capital Measures***.** For social capital measures, three pieces of information were collected directly from the LinkedIn profile page of founders. For the network size, the number of connections listed for each founder on the LinkedIn page was recorded. This is a number listed on the LinkedIn page. The second measure for social capital was endorsements received by a founder by people in his/her network on LinkedIn. For this measure, the number of people from whom the founder received public recommendations on LinkedIn was directly recorded from the profile of the founders. The third measure for social capital was group membership. For this measure, the number of groups the founder is a part of on LinkedIn was recorded directly from the profiles of the founders. The number is publicly available on the LinkedIn page.

Human Capital Measures. Three data points was recorded as indicators of the human capital of a founder. First, the number of years a founder reported having an active professional career. This is a self-reported data that founders provide on LinkedIn. The year in which a founder entered workforce was recorded and the number of years the founder had been professionally active until 2017 was calculated.

As a second measure of human capital, the education level of a founder (in years) was recorded. This is another self-reported data that is provided by founders on LinkedIn. For this measure, the number of years after high school a founder had invested in education was calculated based on the start and end date listed on LinkedIn by founders. For example, if a founder started his/her bachelor’s degree in 1996 and graduated in 2000, the level of education was recorded as 4 years. However, if the same founder went for further studies (for example, graduate school) from 2002 to 2004, then the level of education was recorded as 6 years.

Third, data on the number of skills that were listed on a founder's LinkedIn profile was collected. Skills on LinkedIn are also self-reported data. The number of different skills a founder has was recorded. Some examples of the skills listed were managerial skills, mergers and acquisition, strategic communication, and enterprise software.

Investment Funds Raised. The data on the funds raised by a startup company was acquired on Crunchbase.com. This data is directly available from the database. The funds constituted the money raised by the company through venture capitalists, angel funding agencies, banks, IPOs and other funding sources. The funds raised was then divided by the years survived by the company (the age of the company) to compute a measure of funds raised per year. The age of the company was also available on the Crunchbase database. This procedure was done to control for the age of the company on funds as older companies are likely to have more funds than younger companies.

4.3. Results

Table 5.1 provides the descriptive statistics of the sampled companies from Crunchbase.com, and Table 5.2 summarizes the information on the founders of those companies that was taken from their LinkedIn profiles. As Table 5.1 indicates, the companies (N = 130) raised an average of $2.2 million each year ($SD$ = $3,205,301.1) and had on average 1.75 founders (SD = 0.78). The average number of rounds of investment per company was 2.42 (SD = 1.7), and the mean age of companies was 7.6 years (SD = 5.97).

The 130 companies were founded by 227 founders. As Table 5.2 indicates, on average, the 227 founders had 1,146.68 followers (SD = 1,125.13), had 6.94 endorsements from their connections (SD = 12.52), and were members of 7.27 groups on LinkedIn (SD = 10.31). On average, the founders participated in higher education for 4.42 years (*SD* = 2.84), had 21.64 skills (*SD* = 14.75), and had professional experience (or years worked in industry) for 16.99 years (*SD* = 8.69).

Table 2 Descriptive statistics for funds raised by companies, age of the company, rounds of investments, and number of board members

	N	Mean	SD
Cumulative Funds	130	18,128,429.09	29,728,666.56
Funds per year	130	2,152,032.75	3,205,301.09
Age of the Company	130	7.63	5.97
Rounds of Investment	130	2.42	1.7
Number of Board Members	130	1.75	.78

Table 3 Means and standard deviations of founder human capital variables (skills, education level, years worked in industry) and social capital variables (LinkedIn connections, endorsements, group memberships)

	N	Minimum	Maximum	Median	Mean	SD
LinkedIn Connections	227	0	6,205	791	1,146.68	1,125.13
Endorsements	227	0	148	3	6.94	12.52
Group Memberships	227	0	60	3	7.27	10.31
Skills	227	0	51	22	21.64	14.75
Education Level (in years)	227	0	16	4	4.42	2.84
Years Worked in Industry	227	0	40	17	16.99	8.69

4.3.1. Founder Human Capital, Social Capital, and Startup Funds

The first research question investigated whether a decision strategy that looks at founder social capital better predicts which startup company raised more investment funds than a strategy that ignores social capital cues and only looks at human capital cues. To answer this research question, a series of analyses was done to understand how founder human capital variables, founder social capital variables and startup company investment funds were associated with each other.

In a first step, the study wanted to understand if founder social and human capital variables were positively associated with investment funds raised by a startup company. A correlation was conducted to investigate this question. In the dataset, funds were reported on the company level while the number of followers and founder experience was a characteristic of an individual founder. Most of the companies in the dataset had more than one founder. To address this difference in the unit of analysis, for companies that had more than 1 founder, the founder human and social capital measures were averaged. For example, if a company was founded by three members and the three founders had 100, 300, and 500 followers, respectively, the company's followers would be 300.

For human capital, as can be seen in Table 5.3, there was a positive correlation between work experience (years worked in industry) of a founder and funds raised by a company per year, $r(225)=.21$, $p<.01$. Founder work experience was also positively correlated with cumulative funds raised by a company; $r(225)=.28$, $p<.01$. Other measures of founder human capital–education and skills–were not significantly associated with funds raised by companies. For social capital measures (see Table 5.4), there was a positive correlation between founder LinkedIn connections and funds raised per year by companies, $r(225)=.29$, $p<.01$. The correlation between the cumulative funds raised by companies and founder LinkedIn connections was $r(225)=.22$, $p<.01$. Unexpectedly, group membership of founders (that is, the number of groups a founder was a member of) was negatively associated with the funds raised per year by the company, $r(225)=-.15$, $p<.01$. Group membership was also negatively correlated with cumulative funds, $r(225)=-.19$, $p<.05$. Founder endorsements did not have a significant correlation with funds raised by the company.

Table 4 Correlations among founder human capital variables and funds raised (cumulative and annual) by startup companies

	Funds per Year	Cumulative Funds	Skills	Education Level (in years)	Years Worked in Industry
Funds per Year	--	.92**	.07	.1	.17**
Cumulative Funds		--	.05	.1	.23**
Skills			--	.006	.21**
Education Level (in years)				--	.07
Years Worked in Industry					--

**Correlation is significant at the 0.01 level

* Correlation is significant at the 0.05 level

Table 5 Correlations among founder social capital variables and funds raised (cumulative and per year) by startup companies

		Funds per Year	Cumulative Funds	LinkedIn Connections	Group Memberships	Endorse-ments
Funds per Year		--	.92**	.24**	-.12	.1
Cumulative Funds			--	.18**	-.15*	.05
LinkedIn Connections				--	.32**	.49**
Group Memberships					--	.17**
Endorsements						--

**Correlation is significant at the 0.01 level

* Correlation is significant at the 0.05 level

Taken together, companies with founders who had more work experience, and, had more LinkedIn connections had raised higher investment funds–both annually and cumulatively. Unexpectedly, companies with founders who were part of more LinkedIn groups had raised less investment funds.

To further the analysis and to better understand the relationship between founder human and social capital, a correlation was also conducted between founder human capital and social capital variables. The correlation yielded various significant results (see Table 5.5). Founder LinkedIn connections were positively correlated with founder education levels, $r(225)=.23$, $p<.01$; total number of skills; $r(225)=.43$, $p<.01$; and the work experience of founders, $r(225)=.15$, $p<.05$. Endorsements received by founders was also positively correlated with the total number of skills a founder has; $r(225)=.33$, $p<.0$; and work experience of founders, $r(225)=.25$, $p<.01$. Founder group memberships was only positively correlated with the total number of skills a founder had; $r(225)=.35$, $p<.01$. Founders with high human capital tended to have more LinkedIn connections and endorsements. This was in line with existing studies that have claimed that human capital and social capital were positively correlated with each other (Glaesar, Laibson, & Sacerdote, 2002).

Table 6 Correlations among founder social capital variables and founder human capital variables

	Education (in years)	Skills	Years Worked in Industry	LinkedIn Connections	Endorsements	Group Memberships
Education (in years)	--	.006	.07	.16*	.06	.05
Skills		--	.21**	.4**	.33**	.3**
Years Worked in Industry			--	.16**	.2**	.03
LinkedIn Connections				--	.49**	.24**
Endorsements					--	.17**
Group Memberships						--

**Correlation is significant at the 0.01 level
* Correlation is significant at the 0.05 level

Furthermore, the study also explored if adding founder social capital as a predictor improves the prediction of the amount of funds raised by a company beyond founder human capital. To answer this question, a multiple regression analysis was conducted with the funds raised per year as the criterion variable and three variables constituting founder social capital, and the three variables constituting founder human capital as predictors. The overall regression equation was significant ($F(6,220) = 7.8$, $p<.01$) with an adjusted R^2 of 0.15 (see Table 5.6). Inspection of the individual variables revealed that the mean of founder LinkedIn connections of a company was the strongest predictor ($\beta = .36$, $t(226) = 4.65$, $p<.01$). The mean of years founders have worked in the industry ($\beta = .19$, $t(226) = 2.95$, $p<.01$) and mean of founder group membership ($\beta = -.24$, *t(226)* = -3.68, *p*<.01) were also significant predictors of funds raised by the company per year. The rest of the variables did not significantly improve the prediction of company investment funds when entered together with the other predictors. The strongest predictor of funds raised was the social connectedness of a company, that is, the mean number of LinkedIn connections that founders of a company have.

Table 7 Summary of simple regression analysis for variables predicting funds raised by startup companies per year

	Funds per Year		
Variable	*B*	*SE B*	β
LinkedIn Connections	1305.41	280.71	.36**
Group Memberships	-95773.63	26002.1	-.24**
Endorsements	-27790.3	21133.04	-.01
Education (in years)	55661.28	96053.69	.04
Years in Industry	89825.83	30425.26	.19**
Skills	3848.20	19464.24	.014
R^2	.15		
F	5.01**		

p*<.05,*p*<.01.

4.3.2. Decision Strategies and Startup Success

The first research question asked whether a decision strategy that uses founder social capital makes better investment decisions than a strategy that ignores social capital and only looks at founder human capital. To answer this question, the predictive validities of five decision strategies were determined. The five strategies were *The Human-Capital Strategy*, *the Social-Capital Strategy*, *the Lexicographic Human/Social Capital Strategy*, the *Lexicographic Social/Human Capital Strategy*, and the *Unit Weight Linear Model Strategy* (see Table 3.1). The study found evidence to show that decision-strategies that use founder social capital fare similarly to other strategies that use founder human capital.

The data for each decision strategy was computed at the company level ($N = 130$) for every possible pair-wise comparison totaling 8,385 comparisons. To understand how the different strategies predict different company alternatives based on founder levels of human capital and social capital see Tables (3-9) in Appendix A. In the first step, the founder level data for founder social and human capital was aggregated at the company level. This was done by taking the average of each of the founder human capital and social capital variables for companies that had more than one founder. For example, if a company was founded by three members and the three founders had 100, 300, and 500 LinkedIn connections, respectively, the company's connections would be 300. This process was done for each of the 3 human capital variables and 3 social capital variables.

After all the founder level data was aggregated into company level data, a median split was done for the 6 human and social capital variables. For each variable, the companies were categorized into 2 groups–high (indicated by a 1) and low (indicated by a 0). In the next step, the social capital variables of each company were summed up to provide a social capital score that ranged from 0-3. Similarly, the human capital variables were summed up to provide a human capital score for each company that ranged from 0-3.

For example, if in a pair-wise comparison one founder has higher number of connections, higher number of recommendations, and higher number of group memberships then the overall social capital of the founder was computed as 3 while that of the alternative was computed as 0. In another example, if in a pair-wise comparison, a founder had higher number of connections, lower number of recommendations, and higher number of group memberships, the overall social capital score of the founder was 2 while that of the alternative is computed as 1.

In a final step, the human capital and social capital score of companies which ranged from 0-3 were transformed to provide two dichotomous variables. This was done by grouping companies that had a 0 score for social capital as one group while companies that had a score of 1, 2 or 3 as the second group. Companies that had low social capital had a social capital score of 0 while those that had higher social capital, which ranged from 1-3, had a score of 1. The same process was conducted for the human capital variables for each company. At the end of this computation procedure, there were two dichotomous variables for each company–one for human capital and one for social capital. These variables were then used to model the five decision strategies to show which one best predicted investment funds raised by a startup company.

Table 5.7 provides the discrimination rates and predictive validities of the five different decision models that used founder human capital and social capital variables to predict which company had raised more investment funds. Discrimination rate refers to the percentage of pair-wise comparisons out of the total number of pair-wise comparisons in which a decision-strategy was able to make a choice. Predictive validity refers to the percentage of pair-wise comparisons in which a decision-strategy chose the alternative which had the higher investment funds raised per year.

Table 8 Predictive Validities and Discrimination Rates for the five decision strategies

Decision Strategy	Total Number of Pair-wise Comparisons	Accurately Predicted Cases	Total No. of Cases in which a Prediction was made	Predictive Validity	Discrimination Rate
Human-Capital Strategy	8,385	1,362	2,200	61.9%	26.24%
Social-Capital Strategy	8,385	1,921	3,136	61.26%	37.36%
Unit-Weight Linear Model Strategy	8,385	2,469	4,047	61%	29.45%
Lexicographic Human/Social Strategy	8,385	2,590	4,300	60.23%	51.28%
Lexicographic Social/Human Strategy	8,385	2,601	4,300	60.49%	51.28%
LinkedIn Connections* Strategy	8,385	2,915	4,225	50.39%	68.99%

*****This strategy took only the LinkedIn Connections of a company into consideration while making decisions.

The *Unit-Weight Linear Model Strategy* had a predictive validity of 61%. A predictive validity of over 50% indicates that the model predicts the outcome variable better than random chance. In doing so, the strategy predicted that the company with both high human and high social capital would have raised higher investment funds. This held true for 61% of the pair-wise comparisons of founders where the strategy was able to discriminate between the two companies. This was the base-line decision-strategy.

The *Human-Capital Strategy* had a predictive validity of 61.9%. The *Human-Capital Strategy* took only the human capital of founders into consideration to predict startup investment funds raised. This strategy ignored founder social capital. The *Social-Capital Strategy* had a predictive validity of 61.26%. The one-cue strategies were comparable to the *Unit-Weight Linear Strategy* in predicting startup investment funds. This indicates that less information intensive strategies that use either founder human capital or founder social capital can predict startup investment funds with as much accuracy as a strategy that takes both founder human and social capital into consideration.

The *Lexicographic Social/Human Strategy* was comparable to the *Unit-Weight Model Strategy* with a predictive validity of 60.49%. The *Lexicographic Human/Social Strategy* with a predictive validity of 60.23% was also similar to the rest of the decision strategies in predicting startup investment funds. Therefore, contrary to our expectations the *Lexicographic Human/Social Strategy* did not fare better than the rest of the decision strategies.

As an additional step, this study also looked at a model which only took the social connectedness of founders or the mean number of LinkedIn connections founders of a company have to test the ability of the cue to accurately predict which company raised more investment funds. When analyzing all logical pairs of companies (8,385 pairs) in the current study, the company that had more founder LinkedIn connections also had higher investment funds in 69% (2,915 cases) of the cases (4,225 cases) in which two companies differed in their number of

LinkedIn connections. Therefore, using a decision strategy that only capitalizes on social connectedness was better than the rest of the strategies explored in this study.

In sum, the prescriptive study showed that a strategy that only took social capital into consideration was similar to strategies that took both founder human and social capital into consideration.

4.4. Discussion

The first study looked at whether founder social capital and founder human capital are related to tangible financial outcomes of a startup. Breaking away from the tradition of relying on self-reported ego centered network data, this study utilized social networking site LinkedIn to acquire data on founder social capital and founder human capital. Some social capital and human capital variables of startup founders were associated with tangible financial outcomes of companies. Startup founders with more LinkedIn connections had raised more money for their respective companies. Also, startup founders who had worked more years in the industry raised more funds for their respective companies.

In addition, one of the major takeaways of this study is that social connectedness of a founder is the best predictor of funds raised annually by a founder. Moreover, education level and skills of a founder did not significantly increase the predictability of company funds.

The major question investigated by the first study was whether a decision-strategy which includes founder social capital makes better investment decisions than a decision strategy that only uses founder human capital. The project drew heavily from the decision-making literature and proposed a *Lexicographic Human/Social Capital Strategy* to predict startup investment funds. The proposed strategy first looked at founder human capital of companies and predicted the company with higher human capital will raise more investment funds. In cases where companies were matched in their level of founder human capital, the strategy, in a second step, accessed founder social capital and predicted the company with higher social capital to raise more investment funds. This strategy was compared with four other alternative decision strategies. It was found that the proposed *Lexicographic Human/Social Capital Strategy* reported a predictive validity of 60.23%, which was similar to other decision strategies investigated in the study.

Overall, the analysis showed that decision strategies that take founder social capital into consideration to predict startup investment funds fare similar to decision strategies that use founder human capital or both founder human and social capital cues. The decision strategy that only used founder social capital (*Social Capital strategy*) had a predictive validity of 61.26%. This means, when analyzing all logical pairs of companies in the current study, the company that a higher mean of founder social capital also had higher funds in 61.26% of the cases in which two companies differed in social capital. A 61.26% predictive validity or accuracy based on social capital cues is substantial compared to other information-intensive decision-making models that include more cues, including financial parameters, to predict a start-up's ability to raise investment funds (see Roure & Keeley,1990; Zacharakis & Meyer, 2000). This was similar to other decision strategies that included human capital of founders. In doing so, the study established the importance of founder social capital for investment decisions.

Furthermore, the study also looked at a decision strategy that only took founder social connectedness or the mean number of founder LinkedIn connections of a company into consideration to choose which company had raised more investment funds. The strategy was able to predict the company with higher investment funds in 69% of the pair-wise comparisons where companies differed in their levels of founder social connectedness. The predictive validity of the social connectedness model was, therefore, higher than the rest of the alternative models investigated in this study.

One possible explanation why the predictive validity of just one social capital variable was higher than an aggregate of three social capital variables, could be the negative correlation between founder group membership and investment funds raised by the company. This is contrary to how offline group memberships have been shown to have positive association with organizational outcomes (Bruderl & Prisendorfer, 1999). Research on online social group memberships and organizational outcomes are limited, but the current finding might speak to findings in other interpersonal contexts that show purely online connections have limited benefits, however online spaces help in enhancing and maintaining relationships and communities that have developed in offline spaces (see Lampe, Ellison, Steinfield, 2007; also Reich, Subramanyan & Espinoza, 2012). LinkedIn connections might tend to have positive associations with investment funds raised only when those connections have been made in offline contexts and re-iterated and maintained using an online platform like LinkedIn. However, it has negative association when founders tend to develop connections and/or resources by relying on purely online spaces like LinkedIn groups. Moreover, this finding also indicates that among social capital cues, the number of connections mattered more than any other social capital cues. In other words, one aspect of social capital matters for startup funds while others might not be that important.

What does the findings of the first study mean for founders? The current study provides evidence that data on social networking site LinkedIn is associated with how much money companies raise. Moreover, it is the strongest predictor of startup annual funds. Also, decision strategies that use founder social capital have similar predictive validities than those which use founder human capital. In addition, a model that only takes founder LinkedIn connections into consideration to predict startup investment funds has higher predictive validity than the rest of the strategies. The results prompt the need for more studies that investigate the predictive role of founder social capital on tangible startup outcomes. Correlational studies like this study do not test causal relationships between variables, and, thus, it cannot be concluded from this study that the size of social networks affect funding. However, at the same time, the observed correlations and predictive validities of decision strategies are in accordance with and do not speak against the conventional wisdom that tells founders to invest time and energy into networking and can potentially assist in fundraising efforts. The findings are in accordance with the notion that it is more important who and how many people you know than what you know within the entrepreneurial context. The study accords with the claim that startup founders should invest in building connections on LinkedIn.

Moreover, this study also shows that while LinkedIn networks might represent a limited snapshot of a founder's network, the network is associated with the amount of money a company is able to raise. It also indicates that founders can potentially use the platform to not only build their social connections but communicate the worth of their connectedness to investors.

There are, however, several limitations of this study that can be explored through further research. First, this study looks at limited dimensions of founder social networks. This study focusses solely on the quantity of LinkedIn connections of founders, the number of endorsements they have received, and the number of LinkedIn groups they are members of. This is one of the limitations of using an online resource for analysis. However, there are various issues with self-reported ego network data as well and online resources provide a viable alternative resource to study social networks and their association with tangible organizational outcomes. Future research should investigate other structural properties of founder networks and their relationship with funds raised by the company.

Second, this study does not provide an answer to the question whether more connections lead to more funds or vice versa as the study is merely correlational. Future research can look at longitudinal analysis of founder connections and funds raised by a company. Another limitation of this study is the reliability of data that online resources like LinkedIn and Crunchbase provide. However, online resources do represent the current entrepreneurial environment where communication about networks are often conducted through online platforms. Moreover, given the lack of transparency of financial information available for various startup organizations, crowdsourced information sources like Crunchbase provide more extensive data than other information sources. There is, however, an opportunity for replicating the current study using other information sources to provide a better understanding of the reliability and validity of online information sources.

To conclude, the major contribution of this study is that it extends the study of online social networks in the entrepreneurial context and investment decision-making by looking at the relationship between founder social capital, founder human capital and funds raised by a company. The study shows that founder social capital is a better predictor of company investment funds than founder human capital variables. This study, therefore, provides empirical support for the idea that it is indeed “not what you know, it’s who you know.”

PART II: DESCRIPTIVE APPROACH

CHAPTER 5: FOUNDER HUMAN CAPITAL, SOCIAL CAPITAL AND INVESTMENT DECISIONS

The second part of this project takes a descriptive approach to understand whether taking founder human capital and social capital indicators into account can be used to predict startup outcomes. The descriptive approach, which this section addresses, explores if deciders actually use founder human and social capital indicators to predict startup success. As a second major question, this project aims to explore if the five models described in the first part (see Table 3.1) are descriptive. In other words, how well do the models describe potential investment decisions?

Various studies that have taken a descriptive approach have shown that investors do take founder human capital indicators into consideration while making decisions. For example, Tyebjee and Bruno (1984) conducted structured interviews of 41 venture capital investors and asked them about the evaluation criteria they use to make investment decisions. They classified their open-ended answers into five dimensions which included managerial capability. Managerial capability is often considered a human capital cue (see Bruderl & Prisendorfer, 1999). McMillan, Siegel and Narasimha (1985) further surveyed 100 venture capital investors and showed that venture capital investors look at entrepreneur personality and experience as the most important variable. They further argued that while other important factors like venture plan, competition, product uniqueness were relevant cues for investors, they do not make up for the human capital deficiencies in the entrepreneur.

These studies show that investors do take founder human capital indicators into consideration while making investment decisions, however, they have not taken a decision-making perspective to describe investor decisions. This project takes these findings forward by using various decision strategies to describe investor decisions. Moreover, these studies have not investigated if investors take founder social capital into consideration while making decisions.

The role of founder social capital in investor decision-making is addressed by a separate line of research. This research is limited but a few studies have provided some evidence that investors use founder social capital indicators to make investment decisions. For example, Fried and Hisrich (1994) interviewed and surveyed 18 venture capital investors where investors reported paying attention to founders who were referred by people they knew. Shane and Cable (2002) observed 50 high technology ventures and interviewed 202 seed stage investors and concluded that founders with direct and indirect ties are more likely to be favored by investors. Referrals are often considered as a measure or an outcome of social capital (see Shane & Cable, 2002). However, these studies do not address the question whether the investors place importance on the overall network attributes or social capital of founders. Does the number of connections a founder has is important for investors? Or, does other social capital indicators like endorsements and group memberships matter for investors?

While lacking empirical evidence, there is anecdotal evidence scattered all over popular media where investors and entrepreneurial experts have talked about the importance of entrepreneurial networks to startups and investors. For example, in an editorial published in the Forbes, Martin Zwilling, an investor and expert on startup enterprises, pointed out that successful startup founders are the ones who create deep people connections (Zwilling, 2017). Similarly venture capital investor Chris Fralic has talked about the importance of an entrepreneur’s ability to make connections as an integral part of attracting investments (Upbin, 2013). This has been re-iterated by various other experts, entrepreneurs and investors in various newspaper and magazine articles that argue the importance of entrepreneur networks in attracting investor funding.

The question, however, remains unanswered as to whether investors focus on network attributes of founders when making investment decisions. Does this perceived notion of importance of social networks and founder investment in social capital has a tangible connection with investment funds? This leads to the second research question that this project investigates.

(2) General descriptive question: *Do investors use decision strategies that integrate founder social capital while making investment decisions?*

To answer this question, an experimental study was conducted where investors were provided information about founder LinkedIn human capital and social capital and were asked to make investment decisions in a series of pair-wise choice tasks. In the next step, the five decision strategies used in this project, were used to describe the choices made by the investors.

Furthermore, decision-making research suggests that different groups of deciders may differ in their use of decision-making strategies. For example, experts and novices have been shown to use different decision-strategies in various decision- making contexts. Also, there is some evidence that entrepreneurs approach decision-making problems differently than other groups of deciders. Within the context of investment decisions, this project looks at four different groups of deciders. These are expert investors, expert entrepreneurs, novice investors, and novice entrepreneurs. The primary question was to find out if those four groups differ in their decision-strategies when forming investment decisions.

5.1. Expert and Novice Decision-Making

Research in other organizational contexts suggests that there are two ways in which experts and novices can differ in their decision-making, in their accuracy levels and in the use of information while making decisions. However, the research in both categories seems inconclusive and context-dependent.

For example, researchers have argued that experts make more accurate decisions than novices. However, the research on accuracy levels of experts and novices is inconclusive. Glaeser and Weber (2007) surveyed 215 online brokers and categorized them based on their experience. They concluded that experienced stock brokers made more accurate predictions about the value of their portfolio than less experienced stock brokers. However, this result did not translate into other contexts. For example, Yates, McDaniel and Brown (1991) studied the performance of graduate students (experts) and undergraduate students (novices) and their accuracy of predicting the price and earnings forecasts of publicly listed companies. They found that both experts and novices had moderate accuracy levels with novices outperforming the experts. Does such a pattern hold within the entrepreneurial context? Will there be a difference in how well the five decision-strategies will describe expert and novice investment decisions?

Another way in which experts and novices have been shown to be different in their decision-making process is the amount of information they access to make a decision. However, research here is also inconclusive as some studies have shown experts tend to rely on less information while other studies have reached contrary conclusion and shown that experts use more information than novices. For example, Johnson (1988) looked at security analysts and found that experts use less number of cues to make a decision compared to novices. Davis (1996) (also see Retamero & Dhami, 1996) similarly concluded after studying expert auditors and novices (accounting students) that in a problem-solving task, experts used less cues than novices. However, on the contrary there is evidence from expert and novice bank loan officers (see Andersson, 2004) that show experienced bankers use more information than novices while deciding to sanction a loan. The present study does not directly look at the number of cues used by experts and novices to predict startup success, however, this study looks at strategies that use only founder human capital, or only founder social capital and other strategies that takes both into consideration to make a prediction of investment choice.

In addition, there is some evidence that shows that experts and novices also differ in the pattern of their information search. This has been demonstrated by Jacoby et al. (2001) who showed that security analysts who were experts (who also performed better) used a “within-factor” search for cues. In other words, experts selected an attribute (for example return on sales) for a stock and checked its value for all stocks of interest before moving on to another attribute. Novice deciders, on the other hand, used a “within-stock” information search where they selected one stock and checked the values of all factors available and the moved on to do the same for other stocks. This would imply that experts tend to use an information processing pattern that resembles a lexicographic model where one attribute of all alternatives are accessed at a given time. Novices, on the other hand, are more likely to use linear additive strategies like UWM where all attributes of all alternatives are accessed and then a decision is made. This research also implies that lexicographic models can potentially be more accurate than additive models, given that Jacoby et al. (2001) showed that experts made better decisions by using “within-factor” decision search. The question that the second study addresses is whether there are systematic differences between experts and novices within the entrepreneurial context.

5.2. Entrepreneur and Investor Decision-Making

Additionally, of interest to this project, is the question whether entrepreneurs and investors use different decision strategies to predict startup success using founder social and human capital. Studies have not compared or theoretically proposed different decision-making processes for investors and entrepreneurs. However, some researchers have proposed that entrepreneurs tend to approach problem solving and opportunities differently than other groups. For example, Sarasvathy (2001) has shown that entrepreneurs tend to reject predictive data and resort to more instinctive decision-making techniques. Dew et al. (2001) further provided evidence supporting Saravasthy's (2001) findings and tested the idea on expert entrepreneurs and novices (MBA students). He showed that expert entrepreneurs ignore or report a sense of distrust for predictive information that is obtained from market research methods like surveys, focus groups and other systematic data-based reports.

These findings contrast with the literature that has descriptively looked at investor decision making and have concluded that investors tend to focus on expected rate of return, industry parameters or other predictive information like sales, profits, customers (see Roure & Maidique, 1986; Zacharakis & Meyer, 2000). The takeaway from this literature that is relevant for this study is the finding that entrepreneurs have been shown to have different cognitive processes than investors, however, their decision behaviors have not been simultaneously studied. This project also seeks to explore if there are systematic differences between investors and entrepreneurs as they make investment decisions.

(3) Group-specific descriptive question: *Do investors systematically differ in their decisions from entrepreneurs and are there systematic differences between experts and novices*?

CHAPTER 6: STUDY 2

The second study aimed to further our understanding of founder social capital by exploring if investors and entrepreneurs pay attention to founder social capital while choosing to invest in one company over another. To this end, the five decision strategies–*Unit Weight Linear Model*, *Lexicographic Human/Social Capital Strategy*, *Lexicographic Social/Human Capital Strategy*, *Only Human Capital Strategy*, *Only Social Capital Strategy*–were systematically compared to understand how well they predict the choice behavior of participants.

6.1. Study Design

The study uses four types of LinkedIn profiles. The LinkedIn profiles of founders are chosen from the dataset used in the first study. To choose the LinkedIn profiles, a median split was conducted for all the social capital and human capital variables for each founder. The founders were then arranged in ascending order according to their combined levels of social and human capital. Four types of founder profiles were then selected from the list. The four types were: 1) founder who had high human and high social capital; 2) founder who had high human capital but low social capital; 3) founder who had high social capital but low human capital; and 4) founder who had low human and social capital (see Appendix C for examples of the profiles). Two profiles of each type were selected. The profiles were presented to participants as paired choice tasks. Overall, each participant made pair-wise comparisons of 8 founder LinkedIn profiles yielding a total of 28 forced choice tasks.

6.2. Sample

The second study had four different groups of participants: 10 expert venture capital investors, 10 expert entrepreneurs, 10 finance students (novice investors), and 10 entrepreneurship students (novice entrepreneurs). The overall sample had 40 participants.

Expert Investors. Nine out of the ten expert venture capital investors were seed stage and early stage venture investors, one reported being an early stage and late stage investor. Seven investors reported investing in a combination of industries which included technology/software, agriculture technology, health and life sciences technology. Three investors reported investing across industries. On an average, the investors reported handling about three investments on an annual basis. Six investors were male and four were female. The average age of the investors (*N* = 9) was 38.89 years (*SD* = 8.16). One of the participants did not report their age. All investors reported currently having a LinkedIn account.

Expert entrepreneurs. The average age of the expert entrepreneurs was 38.3 years (*SD* = 10.07; *N* = 10; 9 males, 1 female). As the investors, all entrepreneurs in the study reported having a LinkedIn account. All entrepreneurs had experience in founding or co-founding an entrepreneurial enterprise. On average, they had owned an entrepreneurial enterprise for 9.45 years (*SD*= 7.8) and had 16 employees (*SD*= 10.65). Entrepreneurs reported raising money from the following investors: venture capital investment (four entrepreneurs), bank capital (three entrepreneurs), private equity capital (one entrepreneur), and government funds (one entrepreneurs). Six entrepreneurs reported having used personal funds towards their entrepreneurial enterprises.

Novice Investors. The group of novice investors consisted of students who were pursuing a finance major at Purdue. The average age of the students (seven males and three females) was

20.2 years (*SD* = .78). Five participants were sophomores, three juniors, and two seniors. Nine of the ten novice investors said that they currently had LinkedIn accounts.

Novice Entrepreneurs. Novice entrepreneurs were students who were pursuing a certificate degree in entrepreneurship at Purdue. The average age of the participants (*N* =10) was 20.9 years (*SD* = 1.67). Six participants reported being male, three participants reported being female, one participant chose to not identify their gender. Five participants were sophomores, four juniors, and one a senior. Six out of the ten novice entrepreneurs reported having a current LinkedIn account.

6.3. Procedure

The study was conducted on Qualtrics. Participants accessed and participated in this study on their computers in the location of their choice and were provided with online consent forms at the beginning of the study. In a first step, participants were asked to imagine a scenario where they have to pick a startup company to invest in, from a series of pair-wise comparisons based on the founder LinkedIn profiles. At the beginning of the study, participants were told that they will be presented with eight founders and information from their LinkedIn profiles in a series of 28 pair-wise choice tasks. They were also provided descriptions of the information they would be provided in the choice tasks. They were asked to select the founder whose company the participant will like to invest in; *Based on the LinkedIn information of the following founders, which one of the two companies will you invest in?* The instructions also clarified that all the companies are similar in their financial parameters and capital requirements. These instructions are repeated for each of the 28 choice tasks.

Each choice task consisted of the same steps. Participants were shown two messages on the screen with each consisting of LinkedIn profile information of a startup founder. Each message consisted of two parts–a description of the founder (see Appendix B) and a table that provides information about the LinkedIn profile of the founder. The description did not have any pictures or actual names of entrepreneurs to reduce recognition bias. The table containing information on founder LinkedIn profile contained information about 3 human capital variables and 3 social capital variables. The 3 human capital variables were years of education, years of professional experience, and number of skills a founder has. The 3 social capital cues were number of connections of the founder, number of recommendations the founder has given and received, and the number of LinkedIn groups the founder is a part of. The table also provided descriptions of the companies and educational institutions the founder is from; however, this information was standardized for all the founders so that it does not influence choice behavior. After participants finished all the choice tasks, they were asked to report their liking for each founder and rank the founders based on how successful they think each founder will be in raising investment funds. In the next step, participants were also asked to indicate their perceived level of human capital and social capital for each founder.

At the end of the experiment, participants were provided with a survey that captures descriptive information about the professional experience and expertise levels of all the participants. These surveys are adapted for the four groups of participants. In the next step, all participants were given a questionnaire survey that captured the amount of importance they assign to information available on LinkedIn (see Appendix B). The LinkedIn survey was also adapted for the four groups of participants but capture the same measures. At the end of the survey, participants were asked to provide demographic information.

6.4. Measures

Liking. Participants were asked to indicate their level of liking for each of the 8 founder profiles on a 5-point Likert scale with 1 being “disliked very much” and 5 “liked very much”;

Please indicate how much you liked the company founder profiles (disliked very much to liked very much).

Founder Success. Additionally, participants were asked to indicate how successful they think each founder will be in raising investment funds. *Please indicate the level of success you think these founders will achieve in raising investment funds,* 1 being very low and 5 being very high.

Funds Allocated. Participants were also asked to distribute $1000 among all the 8 founders which served as another measure for participant perception of company success.

Founder Human Capital. Participants were also asked to indicate their perceived level of entrepreneurial knowledge for each founder. *Please indicate the level of entrepreneurial knowledge for each of the founders*, 1 very low and 5 being very high.

Founder Social Capital. Participants were also asked to indicate their perceived level of how well connected they think each of the founders is. *Please indicate how well connected you perceive each founder to be;* 1 being very low to 5 being very high.

Cue Rank. In addition, participants were asked to rank the six human and social capital cues (education levels, skills, work experience, number of connections, endorsements, and group memberships) based on how important they were on their choice decision; *Based on the choices you made, rank these information cues based on how important they were to your decision with 1 being most important and 6 being least important.*

LinkedIn Importance. The importance of LinkedIn for startup enterprises was measured through a five-items on a survey where participants are asked about the importance of LinkedIn profiles, the extent to which the profiles are well developed, the importance of LinkedIn to gain professional recognition, influence, and communicate entrepreneurial expertise (*The next set of* *questions ask you about your perception of how important you think social networking site LinkedIn is for entrepreneurs who are seeking for investments to fund their startups*). The responses are measured on a five-point Likert scale (not important to very important). Participants were also asked if they currently had LinkedIn accounts (yes/no).

6.5. Results

The second study looked at how different groups of decision makers choose companies to invest in based on four different kinds of founder profiles. All the data analysis conducted in this study were idiographic, which means, it was done for each individual participant (see Snook, Dhami & Kavanagh, 2011). The results in the following sections are summarized for different groups of participants and the full sample. Idiographic data analysis is typically used in the psychological research studies that investigate individual decisions like the current study (see Gigerenzer et al., 1999).

The analysis looks at how well the five decision-strategies fit the choices of individual participants. This is referred to as the *strategy fit* of the decision-strategies. The five decision strategies are the same as those used in the first study. They are: 1) *Human-Capital Strategy*; 2) *Social-Capital Strategy*; 3) *Unit Weight Linear Model Strategy*; 4) *Lexicographic Human/Social Strategy*; and 5) *Lexicographic Social/Human Strategy*.

To explain further, each of the five decision-strategies make predictions about which company (of the four types used in this study) will receive investment funds based on their founder profiles in a pair-wise comparison. The predictions are provided in Table 8 (Appendix A). Every participant in this study made 28 choices each. The fit of the decision strategies was computed over all the 28 paired comparisons for all participants, by determining the proportion of participant choices which were accurately predicted by each strategy (see Retamero & Dhami, 2009, for an example).

6.5.1 Decision Strategies to Describe Participant Choice Behavior

The first research question that the project asked was whether investors use decision strategies that integrate founder social capital while making investment decisions. Figure 7.1 shows the strategy fit of the five decision strategies across all the four groups and for each group separately. Overall, the strategy that best described or had the highest fit across all groups was the *Lexicographic Social/Human Strategy*. The strategy matched the decision of participants in 762 of 960 cases where the strategy could make a determination. Therefore, the strategy fit of the model was 79.38%.

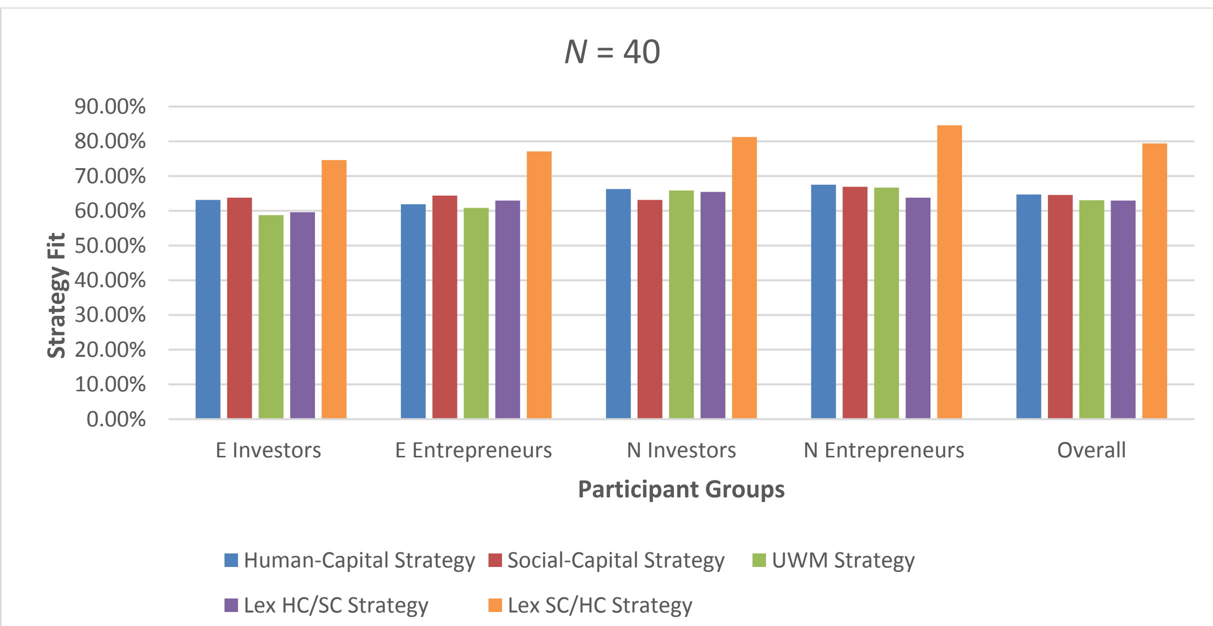

Figure 2 Strategy-fit of the five decision strategies for all participant groups

This was way above that of other strategies analyzed in this study. The strategies that took only one of the cues under consideration – *Human Capital Strategy* had a strategy fit of 64.7% and

Social Capital Strategy was at 64.53%. The *Unit Weight Model Strategy* which looks at the unit sum value of founder human and social capital had a strategy fit of 63.02% which was comparable to that of one-cue based decision-strategies. Contrary to the expectation that participants would first look at human capital of founders and then the social capital of founders to make an investment decision, the *Lexicographic Human/Social Strategy* had predictive validity of 64.69%.

Investor Decisions. Looking at the data separately for each of the four groups of participants, it is seen that the *Lexicographic Social/Human Strategy* best predicted the decisions of expert investors, expert entrepreneurs, novice investors and novice entrepreneurs (see Figure 7.1). Therefore, to answer our first research question, investors do tend to use decision strategies that integrate founder social capital to make investment decisions. For expert investors, the decision-strategy that best predicted or fit investor choices was the *Lexicographic Social/Human Strategy* with a fit of 74.58%. The decision-strategies that had the next highest fit was the *Social-Capital Strategy* at 63.75 and *Human-Capital Strategy* at 63.13%. The *Lexicographic Human/Social Strategy* and *Unit Weight Linear Model Strategy* were the least predictive of all the decision strategies with strategy fits of 59.58% and 58.7% respectively.

Entrepreneur Decisions. The pattern stayed consistent for entrepreneurs. The *Lexicographic Social/Human Strategy* best described entrepreneur choices with a strategy fit of 77.08%. The *Social-Capital Strategy* was the next best at describing entrepreneur decisions with strategy fit of 64.38% followed by *Lexicographic Human/Social Strategy* at 62.92%. The *Human-Capital Strategy* had a strategy fit of 61.88%. The strategy that was the least predictive was the *Unit Weight Model Strategy* at 60.83% (see Figure 7.1).

The second research question that this project investigated was to understand whether investors and entrepreneurs systematically differed in their decision strategies. Also, the third research question that this project investigated was whether experts and novices systematically differed in their investment decisions. Therefore, to understand the differences between the five decision strategies and how they described the decisions of different participant groups, a mixed ANOVA was conducted. The mixed ANOVA compared the strategy fit of participants (DV) with the type of decision-strategy as a within-subject factor (IV) and the type of participant – expert investor, expert entrepreneur, novice investor, novice entrepreneur- as the between-subjects factor (see Retamero & Dhami, 2009 for an example; also see Law, Freer, Hunter & Logie, 2005 for a similar analysis). The analysis showed that there was a significant main effect of type of decision strategy on strategy fit of participants, $F(1.57,56.66) = 21.6$, $p<.001$, $\eta^2 = .38$. Since Mauchly's test of sphericity was violated, the Greenhouse-Geisser correction was used. The *Lexicographic Social/Human Strategy* ($M = 79.38$, $SD = 2.19$) best described or fit the investment choices made by participants across the different groups and surpassed other decision strategies investigated in this study (see Figure 7.2). The interaction effect of type of decision-strategy and type of participant on strategy fit, however, was not significant, $F(4.72,56.66) = .37$, $p=.86$. There were no significant differences between the four different groups of participants and the strategies that best fit their investment choices.

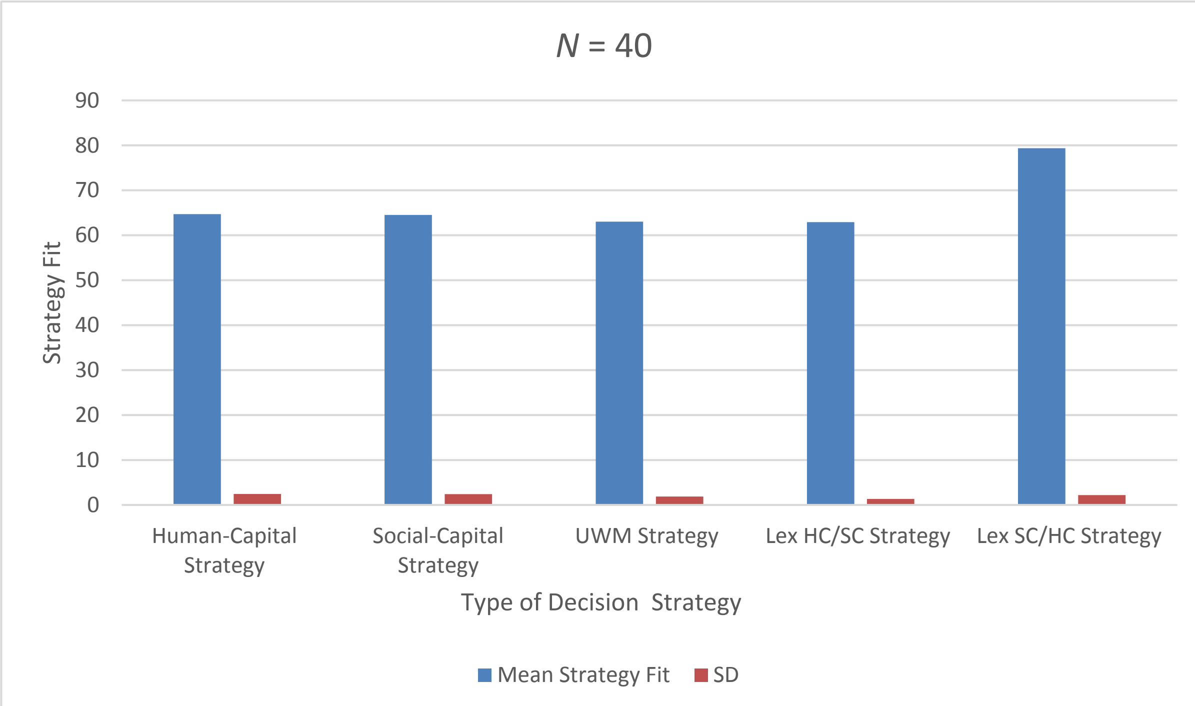

Figure 3 Mean and Standard Deviations of Strategy Fit for Each Decision Strategy

To sum up, investment decisions for all participants could be best described by the *Lexicographic Social/Human Strategy* that first compares the social capital of founders in a pair - wise comparison. In this step, the strategy selects the founder with higher social capital without accessing information about founder human capital. If both alternatives have similar levels of social capital, the strategy then accesses and compares founder human capital. Moreover, both entrepreneur and investor decisions are better explained using one-cue decision strategies rather than strategy like the *Unit Weight Linear Model* that takes both founder social and human capital into consideration simultaneously.

6.5.2 Perceptions of Founder Human and Social Capital

After the choice tasks, participants were also asked to report on their perceived levels of founder human capital and founder social capital for each of the eight founder profiles used in this study. The perceived level of founder human and social capital for the different profiles of founders were used as a manipulation check to see if participants were sensitive to the manipulated levels of founder human and social capital.

Manipulation Check. Table 7.1 (on the next page) and Table 7.2 (on p.62), show the perceived level of founder human capital and social capital for the four kinds of profiles. A repeated measures ANOVA was conducted to compare if there were significant differences among participant groups (IV) for their perceived level of founder human capital and founder social capital (DV) at two levels – high and low. There was a significant main effect of level of founder human capital (high, low) on participant perception of founder human capital; $F(1,36) = 4.51$, $p = .04$, $\eta^2 = .11$. Participants reported higher levels of founder human capital ($M = 3.47$, $SD = .08$) for founders who had high human capital; and lower levels of founder human capital ($M = 3.47$, $SD = .08$) for founders who had low level of human capital.

Table 9 Participant Perceived Level of Founder Human Capital

		E. Investors		E. Entrepreneurs		N. Investors		N. Entrepreneurs	
	N	M	SD	M	SD	M	SD	M	SD
Founder Type 1 (High Human Capital, High Social Capital)	10	3.3	.75	3.65	.53	3.9	.61	3.8	.63
Founder Type 2 (High Human Capital, Low Social Capital)	10	3.15	.71	3.1	.57	3.5	.58	3.35	.71
Founder Type 3 (Low Human Capital, High Social Capital)	10	3.2	.82	3.45	.6	3.7	.54	4	.82
Founder Type 4 (Low Human Capital, High Social Capital)	10	3.1	.81	2.7	.59	2.9	.91	3.25	.86

Also, there was a significant main effect of level of founder social capital on participant perception of founder social capital, $F(1,36) = 31.26$, $p < .001$, $\eta^2 = .47$. Participants reported a higher level of perceived social capital ($M = 3.63$, $SD = .09$) for founders with high social capital than those with low social capital ($M = 3.13$, $SD = .1$). There was no interaction effect between founder human capital level and the type of participant group, $F(3,36) = 1.45$, $p = .24$. The interaction effect between founder social capital level and participant groups was also not found to be significant, $F(3,36) = 1.96$, $p = .1$. Therefore, there were no systematic differences between the reported levels of founder human and social capital between the different groups of participants.

Table 10 Participant Perceived Level of Founder Social Capital

		E. Investors		E. Entrepreneurs		N. Investors		N. Entrepreneurs	
	N	M	SD	M	SD	M	SD	M	SD
Founder Type 1 (High Human Capital, High Social Capital)	10	3.45	.64	4.2	.72	4	.71	4.1	.7
Founder Type 2 (High Human Capital, Low Social Capital)	10	.75	.95	2.8	.63	2.8	.98	2.65	.58
Founder Type 3 (Low Human Capital, High Social Capital)	10	3.1	.77	3.45	.69	3.75	.68	3.95	.72
Founder Type 4 (Low Human Capital, High Social Capital)	10	2.9	.74	2.4	.57	2.9	.81	2.6	.77

Furthermore, for human capital, participants across the four groups, perceived founders to have higher human capital for those founders that had high human capital (M = 3.63, SD =.7) than those that has low human capital (M = 3.13, SD =.73). An independent samples t-test showed that the difference in the perceived level of founder human capital for founders with high and low human capital was significant, *t(158)* = 4.37, *p* <.01.

For social capital, participants across the four groups, perceived founders with higher social capital for those founders that had high social capital (*M* = 3.75, *SD* =.76) than those that had low social capital (*M* = 2.73, *SD* =.75). An independent samples t-test showed that the difference in the perceived level of founder social capital for founders with high and low social capital was significant, *t(158)* = 4.37, *p* <.01.

Therefore, participants across the four groups did perceive founders with high human and social capital to have higher levels of human and social capital respectively than founders who had low human capital and social capital. This means that the manipulation of founder human and social capital used in the four founder profiles were effective.

6.5.3 Liking and Success of Founders

In addition to the choices made by the participants, the study also measured the level of participant liking for each founder and how successful participants perceived every company to be in raising investment funds.

Founder Liking. On a scale of 1-5 where 1 was "disliked very much" and 5 was "liked very much", participants reported their liking for each founder. Founder liking level for each of the four types of founder profiles is provided in Figure 7.3. Participants reported highest level of liking for founders with both high human capital and social capital (*M* = 4.91, *SD* = .93) followed by founders who had high social capital and low human capital (*M* = 4.58, *SD* = .87). Founders with high human and social capital had an average liking level of 4.04 (*SD* = .92) followed by founders who had low human capital and low social capital (*M* = 3.79, *SD* = .71).

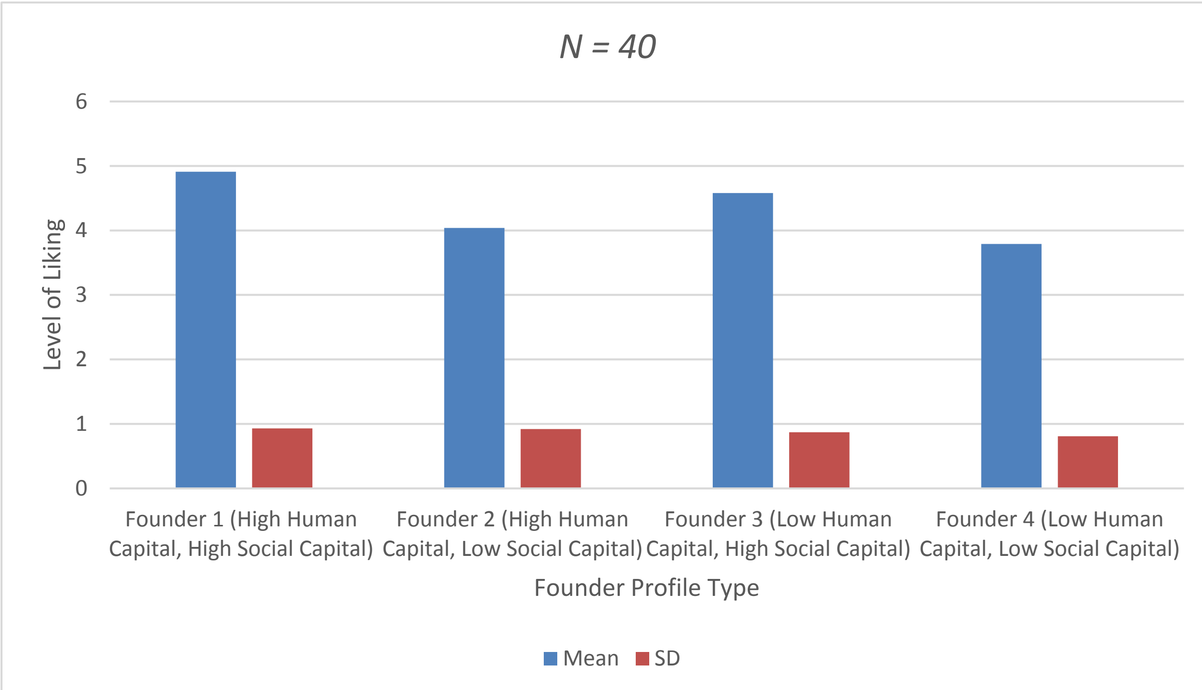

Figure 4 Participant Liking for Different Types of Founder Profiles Used in the Study

To understand if there were significant differences between how much participants liked founders based on their levels of human and social capital, a two-way repeated measures ANOVA was conducted. The ANOVA compared participant liking for founders (DV) where the founder level of human capital and social capital were independent variables. Human capital and social capital had two levels – high and low. There was a significant main effect of founder human capital on participant liking for founders, $F(1,39) = 7.04$, $p = .01$, $\eta^2 = .15$. Participants reported higher level of liking for founders with high human capital ($M = 4.35$, $SD = .1$) than founder with low human capital ($M = 4.18$, $SD = .08$). There was also a significant main effect of founder social capital on participant liking for founders, $F(1,39) = 29.39$, $p < .001$, $\eta^2 = .43$. Participants reported a higher level of liking for founders with high social capital ($M = 4.74$, $SD = .11$) than founders with low social capital ($M = 3.91$, $SD = .1$). The interaction effect of founder human and social capital was not statistically significant, $F(1,39) = .12$, $p = .73$.

Founder Success. Participants were also asked to report the level of success they perceived each founder to be able to achieve in raising investment funds with 1 being very low and 5 being very high. The descriptive statistics for participant perceived level of success for each type of founder is provided in Figure 7.4.

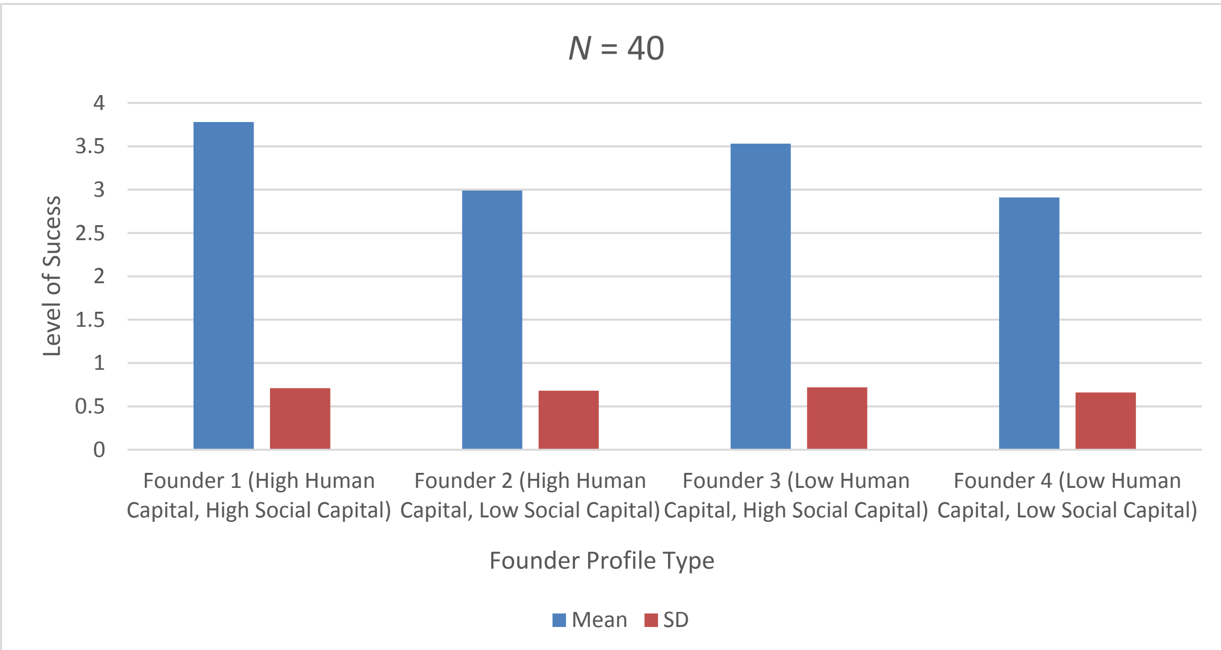

Figure 5 Perceived Levels of Founder Success in Raising Funds for Different Types of Founder Profiles Used in the Study

A two-way repeated measures ANOVA was conducted to compare if participant perception of founder success differed based on founder levels of human and social capital (high and low).The founder profiles used in the study had two differing levels of founder social capital (high and low) and human capital (high and low). The analysis showed that there was a significant main effect of founder human capital on how successful participant perceived a founder to be in raising investment funds, $F(1,39) = 4.37$, $p = .04$, $\eta^2 = .1$. Founders who had high human capital were reported to be more successful ($M = 3.8$, $SD = .07$) than founders who had low human capital ($M = 3.23$, $SD = .08$).

There was also a significant main effect of founder social capital on participant perceptions of founder success, $F(1,39) = 27.12$, $p <.001$, $\eta^2 = .41$. Therefore, founders who had high social capital were perceived to be more successful ($M = 3.65$, $SD = .1$) than founders who had low social capital ($M = 2.96$, $SD = .1$). The interaction effect of founder human and social capital on participant perception of success was not statistically significant, $F(1,39) = .35$, $p = .23$.

Funds Allocated. Participants were also asked to distribute $1000 among all the 8 founders which served as another measure for participant perception of company success. The descriptive statistics for the average amount of funds participants allocated to each type of founder is provided in Figure 7.5.

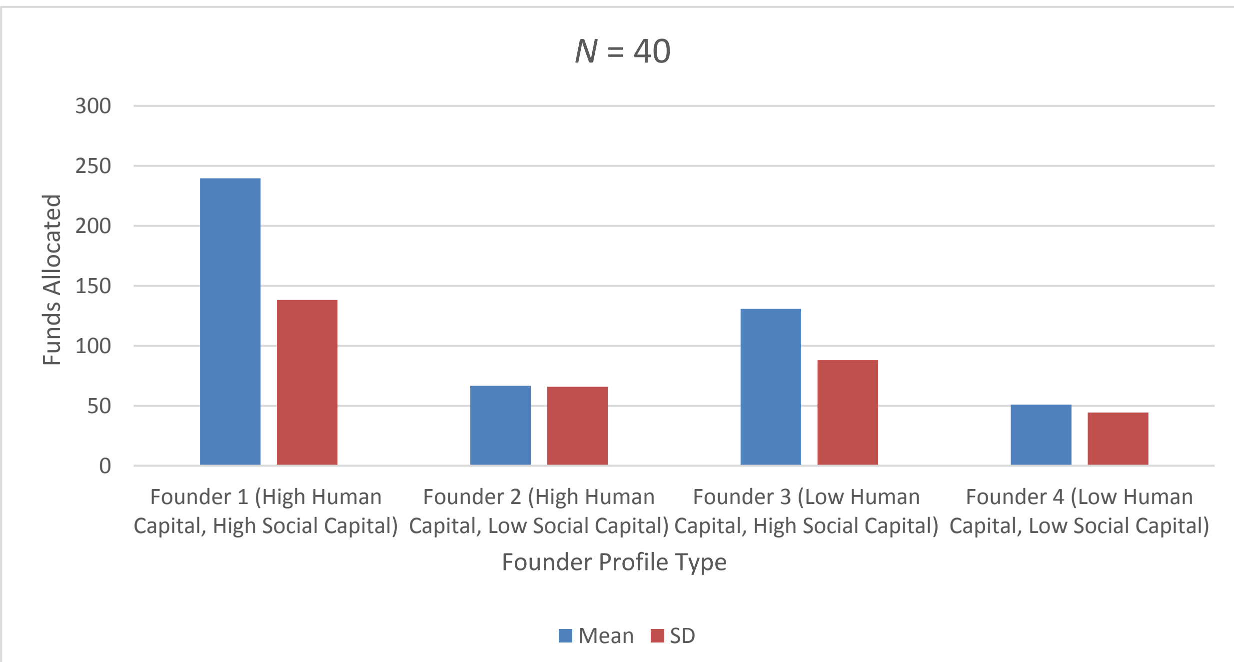

Figure 6 Average Amount of Funds (out of $1000) Allocated to Founders by Participants

A two-way repeated measures ANOVA was conducted to compare the amount of funds participants allocated to founders based on their human capital and social capital levels (low, high). The analysis found that the founder human capital had a significant main effect on the amount of money participants allocated to founders, $F(1,39) = .15.14$, $p < .001$, $\eta^2 = .28$. There was also a significant main effect of founder social capital on amount of funds allocated to founders, $F(1,39) = 75.54$, $p < .001$, $\eta^2 = .66$. Participants allocated more funds to founders who had high human capital ($M = 153.16$, $SD = 8.85$) and high social capital ($M = 185.19$, $SD = 8.48$) than founders who had low human capital ($M = 90.82$, $SD = 8.26$) and low social capital ($M = 50.9$, $SD = 7.02$).

Furthermore, there was also a significant interaction effect between founder human and social capital on participant allocation of funds for founders, $F(1,39) = 6.68$, $p = .014$, $\eta^2 = .15$. Participants allocated more money to founders who had both human capital and high social capital ($M = 153.16$, $SD = 8.85$) compared to founders who had both low human capital and social capital ($M = 153.16$, $SD = 8.85$). However, the main effect of human capital where more money was allocated to the founders who had high human capital only held true when the founder also had high social capital. Participants allocated more money to founders who had low human capital and high social capital ($M = 130.74$, $SD = 13.93$) than those who had high human capital but low social capital ($M = 66.66$, $SD = 10.4$).

6.5.4 Founder Social & Human Capital Cue Ranking

After the choice tasks, participants were asked to rank, in order to importance to their decision, the human capital cues (education level, skills, years worked in industry) and social capital cues (LinkedIn connections, endorsements, group memberships). Table 7.3 provides group-level cue ranking for each of the participant groups. Overall, all participants accorded the highest rank to founder LinkedIn connections ($M = 2.51$, $SD = 1.52$) followed by the number of years a founder has worked in the industry ($M = 2.57$, $SD = 1.63$). The lowest ranked cues were endorsements received by founder ($M = 3.51$, $SD = 1.59$) and LinkedIn group memberships ($M = 5.11$, $SD = .97$). This was consistent across the four groups.

Table 11 Participant Cue Rankings for LinkedIn Human Capital and Social Capital Cues

Cue		E. Investors		E. Entrepreneurs		N. Investors		N. Entrepreneurs	
	N	M	SD	M	SD	M	SD	M	SD
Number of Connections	10	2.89	1.36	2.20	1.48	2.56	2.19	2.44	1.01
Group Membership	10	5.22	.67	5	1.49	5.22	.44	5	1
Endorsements	10	3.78	1.79	3.3	1.42	3.56	1.81	3.44	1.59
Skills	10	3.44	1.94	3.3	1.57	3.78	1.86	4.89	1.69
Work Experience (in years)	10	2.22	1.56	3.3	2.11	2.44	1.13	2.22	1.48
Education (in years)	10	3.44	1.51	3.9	1.2	3.44	1.01	3.00	1.41

Therefore, participants reported the number of founder connections on LinkedIn to be the most important cue for the decisions they made followed by the number of years a founder has worked in the industry. This is consistent with the finding that the *Lexicographic Social/Human Strategy* had the highest predictive validity in describing participant choice behavior.

Moreover, the descriptive cue values are also consistent with the findings in the previous study that took a prescriptive perspective. The prescriptive study (Study 1) revealed that the mean of founder contacts of a company was the strongest predictor, (β = .36, $t(226)$ = 4.65, p<.01) of funds raised by company per year. The mean of years founders have worked in the industry (β = .19, $t(226)$ = 2.95, p<.01) was the next strongest predictor of funds raised by a company per year.

Therefore, founder social capital emerges as an important cue to predict investment funds raised by a company both prescriptively and descriptively.

6.5.5 Perceptions of LinkedIn

The second study also asked participants about their perception of LinkedIn and its use in the entrepreneurial context. The mean of participant perception of importance of LinkedIn to investor-decision-making stood at 2.95 (*SD* =.96). Also, the mean of participant perception of credibility of information on LinkedIn stood at *M* = 3.3 (*SD* =.59). Table 7.4 provides the descriptive statistics for perceived levels of importance of LinkedIn for investors and the how credible they perceived information on LinkedIn to be.

Table 12 Participant perception of Importance of LinkedIn to Investors and Credibility of Information on LinkedIn

		E. Investors		E. Entrepreneurs		N. Investors		N. Entrepreneurs	
	N	M	SD	M	SD	M	SD	M	SD
Importance of LinkedIn to Investors	10	3.3	.48	3.1	1.45	2.7	.82	2.7	.82
Credibility of Information on LinkedIn	10	3.5	.53	3.1	1.45	3.2	.79	3.2	.42

However, participants, across all groups, reported that it was important for founders and startup companies to well-developed profiles on LinkedIn (*M* = 4.4, *SD* = 1.3), communicate about their social influence (*M* = 4.35, *SD* = 1.3), for founders to gain professional recognition (*M* = 4.23, *SD* = 1.6). Descriptive statistics for the four groups are provided in Table 7.5.

Table 13 Participant Perceived Importance of LinkedIn for Startup Founders

		E. Investors		E. Entrepreneurs		N. Investors		N. Entrepreneurs	
	N	M	SD	M	SD	M	SD	M	SD
Importance of Founder Profiles on LinkedIn (for founders)	10	4.3	1.33	4.6	1.08	4.4	1.35	4.3	1.42
Importance of well-developed LinkedIn Founder Profiles	10	4.2	1.03	3.9	1.45	4.1	1.2	4.6	1.58
Importance of LinkedIn as a medium to communicate social influence	10	4.2	1.03	3.4	1.27	4.5	1.51	5.3	.82
Importance of LinkedIn for Professional Recognition	10	4.7	1.64	4	1.83	3.9	1.66	4.3	1.42

6.6. Discussion

Do investors integrate founder social capital cues into consideration when asked to choose between two companies to invest in? The second study provided a clear answer to this question as the *Lexicographic Social/Human Strategy* best predicted the investment decisions of all groups of participants in this study including expert investors. Therefore, in a pair-wise investment task where investors had to choose between two companies, investors first compared the social capital levels of founders. In this step, if a founder had higher social capital than another, the investor chose to invest in the company that had the higher social capital. However, if both companies had founders with similar levels of social capital, only then investors moved on to access and compare the human capital levels of the founders. In the second step, the investors chose the company with founder who had the higher human capital. The strategy fit for the *Lexicographic Social/Human Strategy*, across all groups of participants, was 79.38% which was higher than the rest of the strategies explored in this study. The strategies that took only one of the cues under consideration – *Human Capital Strategy* had a strategy fit of 64.7% and *Social Capital Strategy* was at 64.53%. The *Unit Weight Model Strategy* which looks at the unit sum value of founder human and social capital had a strategy fit of 63.02% which was comparable to that of only one-cue based decision-strategies. Contrary to the expectation that participants would first look at human capital of founders and then the social capital of founders to make an investment decision, the *Lexicographic Human/Social Strategy* had predictive validity of 64.69%. This was contrary to our expectation that *Lexicographic Human/Social Strategy* would be the best strategy to describe investor decisions. However, it did show that investors do integrate founder social capital while deciding which company to invest in. This pattern was consistent across all groups of participants.

Moreover, participants also reported that founder LinkedIn connections was the most important cue that they used while deciding which company to invest in, followed by the number of years a founder had worked in the industry. This was consistent with the findings of the first study where a regression analysis found that founder LinkedIn connections and founder years worked in the industry were the two best predictors of investment funds raised by a startup company. Therefore, the descriptive study replicated the relationship found in the prescriptive study indicating that deciders tend to utilize the most predictive cues available in the environment while deciding to choose which company they should invest in.

The study also showed that decision-making behavior of experts and novices and that of entrepreneurs and investors are very similar. This implies that regardless of the expertise of deciders, social capital is considered across all groups as an important indicator to predict which startup company will gather more investment funds.

The second study indicates that investors are more likely to put more importance on a founder's social connections than a founder's human capital variables like education, work experience or skills. While human capital is still important, investors tend to look at social capital first. The study, therefore, provides empirical support to a largely anecdotal idea that investors value founders who have deep people connections (Zwilling, 2017) and how investors look for founders with social connections as it indicates a founder's ability to raise more investment funds (Upbin, 2013). This study also validates the trend of networking programs in the United States – like startup accelerators – which offer early-stage startups access to social networks and mentorship programs. In 2008, there were only 16 accelerator programs in the United States, however, in 2015 the number has increased to around 170 programs (Hathaway, 2016).

Another takeaway of this study is the use of social media networking site LinkedIn as a medium to understand the role of founder human and social capital and startup investment funds. The founder has been the central figure of entrepreneurial studies for decades. Researchers have asserted that characteristics of founders are more important predictors of startup performance than many financial parameters (Sandberg & Hofer, 1988; Roure & Maidique, 1986). This study supports the idea that the founder is important for predicting the success of a company and its ability to raise investment funds. The study further indicates the role that social media networking site LinkedIn can play in communicating entrepreneur social networks and assist investor decision-making. This study does not assert that investors necessarily look at founder LinkedIn information to make investment decisions, however, it does show that investors are sensitive to cues available on LinkedIn. In other words, LinkedIn can potentially be a medium for entrepreneurs and investors to communicate about their social networks and that it has cues that are associated with startup success variables.

There are various limitations that this study has that can be addressed through future research. First, while this study used information that was derived from actual profiles of LinkedIn founders, this study did not use the actual interface of LinkedIn. The platform contains various other cues that can potentially influence investor decisions. For example, how well developed the profile of a founder is, the actual image of a founder etc. Second, this study restricted its scope by including only quantitative aspects of founder human capital and social capital ignoring the qualitative aspects of these variables. For example, this study only uses the number of founder connections, the number of years of education and work experience, the number of skills, the number of group memberships and endorsements. However, the study did not incorporate qualitative elements like who a founder is connected to, where the founder went to college, who has given the founder endorsements. Further studies can bring the qualitative elements of founder human and social capital to better understand investor decision-making.

Second, the study was also limited in its use of factors that are considered traditionally important for investor decision-making like financial parameters, product information and information about the team rather than just of the founders. While future studies can include various other factors to understand if investors do use founder human and social capital variables combined with other more technical parameters, a strength of this study is its frugality. This study shows that despite not including some traditional financial parameters and product information, the decision-strategies used in this study predicted investor choice behavior with a strategy fit ranging from 63-79%. These validities are comparable to existing investor decision-models that are more information intensive and do not include founder social capital (see Zacharakis & Meyer, 2000).

In sum, the second study provides evidence that investors and other groups of relevant deciders integrate founder social capital variables while making investment decisions and reiterates the importance of social networks of founders in the investor decision-making process.

CHAPTER 7: CONCLUSION AND FUTURE DIRECTIONS

To conclude, the prescriptive (first) study established the importance of founder social capital and its positive association with the amount of investment funds raised by a startup company. The first study found that decision strategies that integrated founder social capital were as good in predicting which company raises more investment funds than strategies that look at only founder human capital or strategies that integrated both founder human and social capital variables. In doing so, the study showed that there is merit for investors to look at founder social capital cues, particularly the number of LinkedIn connections a founder has, while deciding to invest in one company over another.

The descriptive study investigated if investors integrate founder social capital cues when asked to choose between two companies while making investment decisions. The descriptive (second) study showed that the *Lexicographic Social/Human Strategy* best predicted the investment decisions of all groups of participants in the study including expert investors. Therefore, in a pair-wise investment task where investors had to choose between two companies, investors first compared the social capital levels of founders. In this step, if a founder had higher social capital than another, the investor chose to invest in the company that had the higher social capital. However, if both companies had founders with similar levels of social capital, only then investors moved on to access and compare the human capital levels of the founders. In the second step, the investors chose the company with founder who had the higher human capital.

In addition, both studies showed that number of LinkedIn connections, or network size of founders, was the most important cue that predicted the funds raised by a startup company. In the first study a regression analysis found that founder LinkedIn connections and founder years worked in the industry were the two best predictors of investment funds raised by a startup company. This was consistent with the findings of the second study. In the second study, participants reported that founder LinkedIn connections was the most important cue that they used while deciding which company to invest in, followed by the number of years a founder had worked in the industry. Therefore, the descriptive study replicated the relationship found in the prescriptive study indicating that deciders tend to utilize the most predictive cues available in the environment while deciding to choose which company they should invest in.

Another takeaway of this project is the use of social media networking site LinkedIn as a medium to understand the role of founder human and social capital and startup investment funds. This study moves away from the tradition of self-reported network data and utilized the opportunity created by social media networking site LinekdIn.com and crowdfunded database Crunchbase.com to provide empirical evidence that founder social networks are associated with startup outcomes and matter when investors make funding decisions.

Overall, what does it mean for investors and entrepreneurs? Taken together, the two studies re-assert the importance of conventional wisdom and the importance accorded to entrepreneurial networks and their ability in making a new enterprise grow and sustain. The findings of the two studies show that investors are more likely to put more importance on a founder’s social connections than a founder’s human capital variables like education, work experience or skills. While human capital is still important, and is positively correlated with social capital as shown in the first study, investors tend to look at social capital first. Therefore, both the prescriptive and descriptive studies validate the efforts and resources invested by entrepreneurs to establish and grow their entrepreneurial networks.

There are several limitations of this project which can be addressed through future research. First, both the studies use limited dimensions of social and human capital. Both the studies focus solely on the quantity of LinkedIn connections, the number of endorsements they have received, and the number of LinkedIn groups they are members of. Moreover, both the studies also limit the dimensions of human capital which is measured through quantitative parameters (years of education, years of work experience and number of skills). The study does not address the qualitative nature of social capital or human capital. Future studies can further the findings of this project by incorporating the qualitative nature of human capital (for example where founders got their education, which companies they have worked with, and the kinds of skills they have) and social capital (who the founders are connected to, what kind of endorsements they have received, and the kind of groups they are a part of). This will further enhance the understanding of how human and social capital impact startup outcome and investor decision-making.

Second, the studies conducted in this project do not provide an answer to the question whether more connections lead to more funds or vice versa. The first study is merely correlational and the second study does not provide a clear answer to the question. It does show that if a founder has more connections, investors are more likely to invest in the company, however, it does not specify if more connections lead to more investment funds. This limitation can be addressed by longitudinal studies that look into founder social capital indicators and funds raised by companies.

Third, both studies limit the use of factors that are traditionally considered important for startup outcomes and investor decision-making. These factors include financial parameters, product information, and information about the team rather than just the founders. Additional factors can be included in future studies to enhance the findings of this study and get a better understanding of how social and human capital is associated with startup outcomes and investor decisions.

However, while future studies can expand on the findings of the current studies, the aforementioned limitations also attest to one of the strengths of this project which lies in its frugality. The studies in this project show that despite not including some traditional financial parameters and product information, the decision-strategies used in this study predicted investor choice behavior with a strategy fit ranging from 63-79%. These validities are comparable to existing investor decision-models that are more information intensive and do not include founder social capital (see Zacharakis & Meyer, 2000).

To conclude, the major contribution of this project is that it extends the study of online social networks in the entrepreneurial context and investment decision-making by looking at the relationship between founder social capital, founder human capital and funds raised by a company. The study brings the decision-making perspective to understand whether founder human and social capital can be used to predict startup investment funds. The project provides a prescriptive as well as a descriptive perspective. In doing so, this study shows that founder social capital, specifically the number of founder LinkedIn connections, is a better predictor of company investment funds than founder human capital variables. Moreover, this project provides evidence that investors and other groups of relevant deciders integrate founder social capital variables while making investment decisions. This project, therefore, provides empirical support, both prescriptively and descriptively, for the largely anecdotal idea that it is indeed “not what you know, it’s who you know.”

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APPENDIX A

Table 14 Research Questions

Prescriptive Approach	
RQ1	Does a decision strategy that looks at social capital better predict startup investment funds than a strategy that ignores social capital cues and only looks at human capital cues?
Descriptive Approach	
RQ*2*	Do investors use decision strategies that integrate founder social capital while making investment decisions?
RQ4	Do investors systematically differ in their decisions from entrepreneurs and are there systematic differences between experts and novices?

Table 15 The four types of LinkedIn Profiles for Descriptive Study (Study 2)

Profile Types	Founder Name	Human Capital	Social Capital
Profile 1(Company Red)	Chris Red	High (Unit weight sum of education level, professional experience, number of skills)	High (Unit weight sum of connections, group memberships, recommendations)
Profile 2 (Company Brown)	Dan Brown	High (Unit Weight Sum of education level, professional experience, number of skills)	Low (Unit weight sum of connections, group memberships, recommendations)
Profile 3 (Company Crimson)	Steve Crimson	Low (Unit Weight Sum of education level, professional experience, number of skills)	High (Unit weight sum of connections, group memberships, recommendations)
Profile 4 (Company Blue)	Mark Blue	Low (Unit Weight Sum of education level, professional experience, number of skills)	Low (Unit weight sum of connections, group memberships, recommendations)

Table 16 Pair-wise comparison of founder profiles and predictions using Unit Weight Linear Decision Model

	Company 1		Vs	Company 2		Unit Weight Linear Model
Founder	Human Capital	Social Capital	Founder	Human Capital	Social Capital	Prediction
Chris	High	High	Dan	High	Low	Chris
Chris	High	High	Steve	Low	High	Chris
Chris	High	High	Mark	Low	Low	Chris
Dan	High	Low	Steve	Low`	High	Not Applicable
Dan	High	Low	Mark	Low	Low	Dan
Steve	Low	High	Mark	Low	Low	Steve
Dan	High	Low	Chris	High	High	Chris
Steve	Low	High	Chris	High	High	Chris
Mark	Low	Low	Chris	High	High	Chris
Steve	Low	High	Dan	High	Low	Not Applicable
Mark	Low	Low	Dan	High	Low	Dan
Mark	Low	Low	Steve	Low	High	Steve
% of cases where the decision strategy makes a decision = 83.33%						

Table 17 Pair-wise comparison of founder profiles and predictions for Lexicographic Human/Social Capital Strategy

	Company 1		Vs	Company 2		Lexicographic Model 1
Founder	Human Capital	Social Capital	Founder	Human Capital	Social Capital	Prediction
Chris	High	High	Dan	High	Low	Chris
Chris	High	High	Steve	Low	High	Chris
Chris	High	High	Mark	Low	Low	Chris
Dan	High	Low	Steve	Low`	High	Dan
Dan	High	Low	Mark	Low	Low	Dan
Steve	Low	High	Mark	Low	Low	Steve
Dan	High	Low	Chris	High	High	Chris
Steve	Low	High	Chris	High	High	Chris
Mark	Low	Low	Chris	High	High	Chris
Steve	Low	High	Dan	High	Low	Dan
Mark	Low	Low	Dan	High	Low	Dan
Mark	Low	Low	Steve	Low	High	Steve
% of cases where the decision strategy makes a decision = 100%						

Table 18 Pair-wise comparison of founder profiles and predictions for Lexicographic Social/Human Capital Strategy

	Company 1		Vs	Company 2		Lexicographic Model 2
Founder	Human Capital	Social Capital	Founder	Human Capital	Social Capital	Prediction
Chris	High	High	Dan	High	Low	Chris
Chris	High	High	Steve	Low	High	Chris
Chris	High	High	Mark	Low	Low	Chris
Dan	High	Low	Steve	Low`	High	Steve
Dan	High	Low	Mark	Low	Low	Dan
Steve	Low	High	Mark	Low	Low	Steve
Dan	High	Low	Chris	High	High	Chris
Steve	Low	High	Chris	High	High	Chris
Mark	Low	Low	Chris	High	High	Chris
Steve	Low	High	Dan	High	Low	Steve
Mark	Low	Low	Dan	High	Low	Dan
Mark	Low	Low	Steve	Low	High	Steve
% of cases where the decision strategy makes a decision = 100%						

Table 19 Pair-wise comparison of founder profiles and predictions using Human Capital Strategy

	Company 1		Vs	Company 2		Founder Human Capital Model
Founder	Human Capital	Social Capital	Founder	Human Capital	Social Capital	Prediction
Chris	High	High	Dan	High	Low	Not Applicable
Chris	High	High	Steve	Low	High	Chris
Chris	High	High	Mark	Low	Low	Chris
Dan	High	Low	Steve	Low`	High	Dan
Dan	High	Low	Mark	Low	Low	Dan
Steve	Low	High	Mark	Low	Low	Not Applicable
Dan	High	Low	Chris	High	High	Not Applicable
Steve	Low	High	Chris	High	High	Chris
Mark	Low	Low	Chris	High	High	Chris
Steve	Low	High	Dan	High	Low	Dan
Mark	Low	Low	Dan	High	Low	Dan
Mark	Low	Low	Steve	Low	High	Not Applicable
% of cases where the decision strategy makes a decision = 66.67%						

Table 20 Pair-wise comparison of founder profiles and predictions using only Social Capital Strategy

	Company 1		Vs	Company 2		Founder Social Capital Model
Founder	Human Capital	Social Capital	Founder	Human Capital	Social Capital	Prediction
Chris	High	High	Dan	High	Low	Chris
Chris	High	High	Steve	Low	High	Not Applicable
Chris	High	High	Mark	Low	Low	Chris
Dan	High	Low	Steve	Low`	High	Steve
Dan	High	Low	Mark	Low	Low	Not Applicable
Steve	Low	High	Mark	Low	Low	Steve
Dan	High	Low	Chris	High	High	Chris
Steve	Low	High	Chris	High	High	Not Applicable
Mark	Low	Low	Chris	High	High	Chris
Steve	Low	High	Dan	High	Low	Steve
Mark	Low	Low	Dan	High	Low	Not Applicable
Mark	Low	Low	Steve	Low	High	Steve
% of cases where the decision strategy makes a decision = 66.67%						

Table 21 Pair-wise comparison of the predictions made by the decision strategies

Decision Strategies	% of cases they have the same prediction	% of cases they have the different decision
Unit Weight Linear Model **X** Lexicographic Human/Social Capital Strategy	83.3%	16.67%
Unit Weight Linear Model **X** Lexicographic Social/Human Capital Strategy	83.3%	16.67%
Unit Weight Linear Model **X** Human Capital Strategy	50%	50%
Unit Weight Linear Model **X** Social Capital Strategy	50%	50%
Lexicographic Human/Social Capital Strategy **X** Lexicographic Social/Human Capital Strategy	83.3%	16.67%
Lexicographic Human/Social Capital Strategy **X** Human Capital Strategy	66.67%	33.33%
Lexicographic Human/Social Capital Strategy **X** Social Capital Strategy	50%	50%
Lexicographic Social/Human Capital Strategy **X** Human Capital Strategy	50%	50%
Lexicographic Social/Human Capital Strategy **X** Social Capital Strategy	66.6%	33.33%
Human Capital Strategy **X** Social Capital Strategy	16.67%	83.33%

APPENDIX B

1. Snapshots of the LinkedIn profiles that would be provided to participants

a. **High Human Capital, High Social Capital**

Company Red

Founder: Chris Red

Description:

Chris is the founder of a technological startup company. Chris describes himself as a digital innovator and entrepreneur. Chris completed his higher education at a midwestern university in the United States. Chris has various interests that include new and innovative technologies, business and management; and marketing trends. Chris has worked in companies that have a focus on entrepreneurial technologies.

More information available on Chris's LinkedIn profile is provided below.

Number of Connections	**500 and above**
Group Memberships	**13**
Recommendations Received	**99**
Work Experience (in years)	**27**
Education (in years)	**7**
Skills	**50**

b. **Low Human Capital, Low Social Capital**

Company Blue

Founder: Mark Blue

Description:

Mark is the founder of a technological startup company. Mark describes as technologically savvy and a seasoned manager. Mark completed his higher education at a university in the East Coast of United States. Mark has various interests that include management consulting, customer relations, and technological advancements. Mark has worked with various companies and projects that focus on technological products.

More information available on Mark's LinkedIn profile is provided below.

Number of Connections	**191**
Group Memberships	**0**
Recommendations Given	**1**
Recommendations Received	**1**
Work Experience	**24**
Education (in years)	**4**
Skills	**0**

c. **Low Human Capital, High Social Capital**

Company Name: Crimson

Founder: Steve Crimson

Steve is the founder of a technological startup company. Steve described himself as a leadership and management expert for entrepreneurial enterprises. Steve completed his higher education at a university in the Pacific North West of the United States. Steve has various interests that include leadership training, management and new technologies. Steve has worked with companies that have specialized in information and technology services.

More information available on Steve's LinkedIn profile is provided below.

Number of Connections	**500 and above**
Group Memberships	**19**
Recommendations Received	**5**
Work Experience	**19**
Education (in years)	**4**
Skills	**0**

d. **High Human Capital, Low Social Capital**

Company Brown
Founder: Dan Brown

Dan is the founder of a technological startup company. Dan describes himself as technological innovator and entrepreneur. Dan completed his higher education at a university located on the North-east of the United States. Dan has various interests that include leadership training, new technologies, and business relations. Dan has worked with companies that have specialized in technological advancement and services.

More information available on Dan's LinkedIn profile is provided below.

Number of Connections	**362**
Group Memberships	**0**
Recommendations Received	**0**
Work Experience	**14**
Education (in years)	**4**
Skills	**30**

Classification Questionnaire

The following set of questionnaires is for classification purposes.

1. Which of the following do you identify as:
   a. Investor
   b. Entrepreneur
   c. Student

Questionnaire 1 (Investor)

If you are an investor, please answer the following questions. If you are not an investor, please proceed to the next questionnaire.

1. What sort of investor are you or the investment company you represent?
   a. Venture Capital
   b. Corporate Venture Capital
   c. Bank
   d. Angel Investor
   e. Private Equity Investor
   f. Accelerator
   g. Crowdfund investor
   h. Micro VC
   i. Government or a government affiliated organization (e.g. educational institution)

2. In what industries do you/your company invest? TEXT ANSWER
3. At what stages do you or your company invest in startup companies? Check all that apply.
   a. Seed Phase
   b. Early Stage
   c. Late Stage
   d. Private Equity
4. What is the average number of investments you manage in a year?
   a. None
   b. 1-5
   c. 5-10
   d. Over 10

5. If you represent an investment company, what is the average number of investments your company has manages in a year?
   a) 1-10
   b) 11-20
   c) 21-30
   d) 31-40
   e) 41-50

f) Above 50

6. Please provide the number of years you have been an investor or worked with an investment company? TEXT ANSWER
7. Please indicate your perceived levels of expertise in startup investments (1. Very High, 2. High, 3. Moderate, 4 Low, 5 Very low)

Questionnaire 2 (Entrepreneur)

If you are an entrepreneur, please provide the following information.

1. Do you currently own/co-own an entrepreneurial enterprise? Yes/No
2. Have you ever owned/co-owned an entrepreneurial enterprise in the past? Yes/No
3. How many years have you owned/co-owned an entrepreneurial enterprise? TEXT ANSWER
4. Please provide the industry which your startup venture belongs? TEXT ENTRY
5. What is the number of employees that your current venture has? TEXT ENTRY
6. Which of the following sources have you used to raise investment funds? Check all that apply.
    a. Venture Capital
    b. Corporate Venture Capital
    c. Bank
    d. Angel Investor
    e. Private Equity Investor
    f. Accelerator
    g. Crowdfund investor
    h. Micro VC
    i. Government or a government affiliated organization (e.g. educational institution)
7. If you have received funding from a venture capital investor or a corporate venture capital organization, what phase did you get the said funding.
    a. Seed Stage
    b. Early Stage
    c. Late Stage
    d. Private Equity
8. Please indicate your perceived level of expertise in entrepreneurial enterprises and processes. (1. Very High, 2. High, 3. Moderate, 4 Low, 5 Very low)

Questionnaire 3 (Students)

If you are currently a student, please answer the following questions.

1. Are you a:
    a. Freshmen
    b. Sophomore
    c. Junior
    d. Senior
    e. Graduate Student
    f. Other
2. What is your major? TEXT ENTRY
3. Have you taken any classes that have covered financial investments? Yes/No
4. If yes, please indicate the number of course credits you have taken in classes related to financial investments? TEXT ENTRY
5. Have you received the Purdue Entrepreneurial Education Certificate? Yes/No
6. Please indicate your level of expertise in financial investments? (1. Very High, 2. High, 3. Moderate, 4 Low, 5 Very low)
7. Please indicate your level of expertise in entrepreneurial enterprises and processes? (1. Very High, 2. High, 3. Moderate, 4 Low, 5 Very low)

Questionnaire 4 (The use of LinkedIn)

The following section is divided into 5 parts. You will be asked about your LinkedIn usage; your perception of how important LinkedIn information is for startups and investment decision-making. You will also be asked about the sources of information investors use to make investment decisions.

Part 1: LinkedIn Usage

Investor Prompt: The first set of questions in this section will ask you about your usage of social networking site LinkedIn.

Entrepreneur Prompt: Same prompt.

Student Prompt: Same prompt.

1. Do you have a LinkedIn Account? (Yes, No)
2. How often do you visit Social Networking websites? (1. Very frequently; 2. Occasionally; 3. Rarely; 4. Very Rarely; 5. Never)
3. How often do you use LinkedIn? (1. Very frequently; 2. Occasionally; 3. Rarely; 4. Very Rarely; 5. Never)
4. How often do you interact with others through LinkedIn? (1. Very frequently; 2. Occasionally; 3. Rarely; 4. Very Rarely; 5. Never)

5. How often do you post information on LinkedIn? (1. Very frequently; 2. Occasionally; 3. Rarely; 4. Very Rarely; 5. Never)
6. How often do you access information on LinkedIn? (1. Very frequently; 2. Occasionally; 3. Rarely; 4. Very Rarely; 5. Never)
7. How often do you engage in the information or people available on LinkedIn groups? (1. Very frequently; 2. Occasionally; 3. Rarely; 4. Very Rarely; 5. Never)
8. How many groups on LinkedIn are you a part of
    a. 0
    b. 1-5
    c. 6-10
    d. 11-15
    e. 15-20
    f. Over 20

Part 2: Criteria for Investment Decisions

Investor prompt: In the following questions, you are asked about the criteria you use while making investment decisions.

Entrepreneur Prompt/ Student Prompt: In the following questions, you are asked about the criteria you think investors use while making funding decisions.

How much do the following criteria influence an investor's financial decisions in favor or against a startup company?

All questions are measured on a scale where 1 is not at all and 5 is very strongly.

a. Industry of the startup company
b. Market Potential of the product
c. Uniqueness of the product
d. Growth potential of the industry
e. Online presence of the startup company
f. Educational credentials of the founders
g. Professional experience of the founders
h. How well connected the founders are with people in the industry
i. How well connected founders are with people outside the industry
j. Founder referrals
k. Skills or technical capabilities of the founders
l. How active founders are in entrepreneurial networking events
m. OTHER (Comment/ text option)

Part 3: ***Importance of LinkedIn for startups***

Investor prompt: The next set of questions ask you about your perception of how important you think social networking site LinkedIn is for entrepreneurs who are seeking for investments to fund their startups.

Entrepreneur Prompt/Student Prompt: Same prompt.

All questions are measured on a scale where 1 is not important and 5 is very important.

1. How important is it for a startup founder to have a well-developed LinkedIn profile?
2. How important is it for a startup company to have a LinkedIn profile?
3. How important is LinkedIn to gain professional recognition?
4. How important is LinkedIn presence for influencing others in a professional network?
5. How important is LinkedIn for communicating entrepreneurial expertise?

Part 4: ***Use of Information on LinkedIn***

Investor Prompt: The next set of questions asks about your perception and the importance you associate with the information provided on social media networking site LinkedIn.

Entrepreneur Prompt/ Student Prompt: Same as investor prompt.

9. How important are LinkedIn profiles of founders as a source of information for startup investors? (1. Not at all important; 2. Somewhat important; 3. Moderately Important; 4. Very Important; 5. Extremely Important)

10. I: How often do you access the LinkedIn profiles of entrepreneurs while choosing among startup investment proposals? (1. Very frequently; 2. Occasionally; 3. Rarely; 4. Very Rarely; 5. Never)
    E: How often do you think investors access LinkedIn profiles of entrepreneurs while choosing among startup investment proposals. (1. Very frequently; 2. Occasionally; 3. Rarely; 4. Very Rarely; 5. Never)

11. There are various types of information available on LinkedIn in an individual entrepreneur's profile. How important are the following information available on LinkedIn to predict startup success? All questions are measured on a scale where 1 is not important and 5 is very important.
    a. The number of connections a founder has
    b. The number of endorsements a founder has
    c. The education level and certifications listed by the founder
    d. The presence of the startup company on LinkedIn
    e. Honors and Awards listed by the founder
    f. Professional experience (including companies worked in) by the founder
    g. Mutual connections between you and the founder
    h. The number of groups a founder is a member of
    i. Skills listed by the founder
    j. Activity levels of the founder on LinkedIn and LinkedIn groups (posts, comments, media links etc.)
    k. How well developed and professional the founder's profile is
    l. Recommendations received by the founder

m. Recommendations given by the founder to his/her connections
n. Whether the founder has a premium LinkedIn account

12. How credible is the information available on LinkedIn? (1. Very high credibility; 2. High credible; 3. Moderate credibility; 4. Low credibility 5. Very low credibility)

13. How useful is LinkedIn as a source of online conversation and/or interaction? (1. Very useful; 2. Useful; 3. Somewhat useful; 4. Not useful; 5. Never useful)

14. I: How often do you seek out LinkedIn profiles of entrepreneurs while screening for investment opportunities? (1. Extremely often, 2. Very often, 3. Moderately often, 4. Rarely, 5. Never).

15. E: How often do you think investors seek out LinkedIn profiles of entrepreneurs while screening for investment opportunities? (1. Very frequently; 2. Occasionally; 3. Rarely; 4. Very Rarely; 5. Never)

16. How important is the information available on LinkedIn for deciding whether to invest in a startup company? (1. Not at all important; 2. Somewhat important; 3. Moderately Important; 4. Very Important; 5. Extremely Important)

Part 5: *Investor Decision Making*

Investor prompt: The next set of questions are open-ended questions about the sources of information you use during the investment decision-making process.

Entrepreneur prompt/ Student Prompt: The next set of questions are open-ended questions about the sources of information investors use while making investment decisions. As an entrepreneur, based on your experience with investors, please answer the following questions.

1. I: Please comment on the major sources of information you use while making an investment decision?
   E: Based on your experience and understanding, please comment on the major sources of information investors use to make an investment decision.

2. I: Please comment on the process of information search you conduct while choosing a startup company to invest in?
   E: Based on your experience and understanding, please comment on the process of information search investors conduct while choosing a startup company to invest in?

3. I: Please comment on the sources of information through which you hear about the companies that you eventually invest in?
   E: Based on your experience and understanding, please comment on the sources of information you utilize or plan to use to publicize your company to an investor?

4. I: Please comment on the role of social networking sites (Twitter, Facebook, LinkedIn) in investment decision-making process?
   E: Based on your experience and understanding, please comment on the role of social networking sites (Twitter, Facebook, LinkedIn) in investment decision-making process?

5. I: Please comment on the role of social networking sites (Twitter, Facebook, LinkedIn) in the entrepreneurial process (setting up a startup company)?
   E: Please comment on the role of social networking sites (Twitter, Facebook, LinkedIn) in the entrepreneurial process (setting up a startup company)?

Questionnaire 5 (Demographic Information)

In this section, you will be asked few demographic questions.

1. Please identify your gender
   a. Male
   b. Female
2. What age group do you belong to?
   a. 18-24 years
   b. 25-34 years
   c. 35-49 years
   d. 50-59 years
   e. 60-69 years
   f. 70 and above
3. Please indicate your education level or the highest degree you are currently pursuing?
   a. Higher education, non-degree qualification
   b. Vocational qualification
   c. University graduate degree
   d. University post graduate degree or higher
   e. Other
4. Which of the following best describes your employment status?
   a. Full time
   b. Part time
   c. Non-employed
   d. Student
   e. Other