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Looking Backward and Forward? Understanding the Role of Temporal Focus on Startup Performance

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Abstract

In this study we look at the relationship of perception of time and self with performance in the context of startups. By relying on solid constructs from psychology, namely temporal focus (the degree to which individuals characteristically devote attention to perceptions of the past, present, and future), construals (future events can be construed in a higher-level construal, thus forming abstract representations or low level construals, which are more concrete and specific) and self categorization which can be (collective or individualistic) we can predict startup performance. Through novel datasets such as Crunchbase and Twitter we analyze perceptions of 2111 startup founders and 620 startup teams. Twitter data provides fine-grained, longitudinal, spontaneous and conversational type of data. From content-analyzing this data, we find high past focus, low future focus, high collective self-categorization and lower level construal to be associated with better performance. These results hold true at the team level, demonstrating the importance of perceptional biases in new venture performance.

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ABSTRACT

In this study we look at the relationship of perception of time and self with performance in the context of startups. By relying on solid constructs from psychology, namely temporal focus (the degree to which individuals characteristically devote attention to perceptions of the past, present, and future), construals (future events can be construed in a higher-level construal, thus forming abstract representations or low level construals, which are more concrete and specific) and self categorization which can be (collective or individualistic) we can predict startup performance. Through novel datasets such as Crunchbase and Twitter we analyze perceptions of 2111 startup founders and 620 startup teams. Twitter data provides fine-grained, longitudinal, spontaneous and conversational type of data. From content-analyzing this data, we find high past focus, low future focus, high collective self-categorization and lower level construal to be associated with better performance. These results hold true at the team level, demonstrating the importance of perceptional biases in new venture performance.

INTRODUCTION

Entrepreneurs are constantly navigating through not only changing spatial boundaries but also temporal boundaries. By understanding differences in how these boundaries are perceived we can better understand differences in strategic choice, which in turn explains performance differences. In particular, a entrepreneur perception of time plays a compelling role in decisions such as what ideas are pursued, what types of markets are explored, what type of deadlines are adhered too and many other important choices made in the life of a startup. Startup founders are constantly trying to resolve the exploration exploitation dilemma and they encounter substantial uncertainty from different dimensions, and hazards due to rapid technological development and obsolescence (Shane & Venkataraman, 2000). Thus startup founders are constantly faced with ambiguity and susceptibility to failure. Understanding performance differences of startups contributes strongly to management theory (Gimeno, Folta, Cooper, & Woo, 1997).

Several researchers have tried to understand differences in entrepreneurial venture performance (Aldrich & Martinez, 2001; Baron, 2004; Shane & Venkataraman, 2000). To understand where differences in performance come from, tracing the origins of individual's cognitive and temporal resources is essential. "Language is the most common and reliable way for people to translate their internal thoughts and emotions into a form that others can understand" (Tausczik & Pennebaker, 2010). Empirically we build on language to capture perceptions of entrepreneurs we are able to understand their cognition, personality. By doing so we can capture who they are, the social relationships they are in which in turn affect their decision-making. Research has found that entrepreneurs goals and communicated vision have a direct effect on venture growth (Baum

& Locke, 2004). Intrinsically linked to both goals and communicated vision is our perception of time, self vs. others, and the way we use to construct our messages. Several studies have bolstered the importance of studying the subjective perception of time and self to advance research in strategy (Ancona, Okhuysen, & Perlow, 2001; Mosakowski & Earley, 2000). Research in strategy has emphasized that "Important decisions often result from deliberate attempts to anticipate future environments" (Gavetti, Greve, Levinthal, & Ocasio, 2012, page 9). A critical determinant of performance of startups rests on startup founder's ability to construct past experience and envision their future, to categorize themselves and others in their teams, and to devote their attention to either past, present or future issues. Despite the importance of the subjective perception, there have been few studies, which have looked at these variables of interest of time focus or self-perception. And more importantly even fewer studies have tried to understand the association of these variables with entrepreneurial performance.

Funding raised is a good proxy for entrepreneurial performance (Samila & Sorenson, 2011). Funding at different stages has been instrumental for growth of firms such as Microsoft, Oracle to name a few. Funding can occur at various stages of a startup, seed is usually the first type of funding a new startup would secure, startup investments and finally expansion investments that happen at a later stage. The criteria used by venture capitalist's in making funding decisions are the idea or opportunity, the market, the management team, and the entrepreneur making the pitch (Chen, Yao, & Kotha, 2009). Chen and coauthors also have pointed out that funding decisions can be based on the technical, personal, and interpersonal capabilities of the startup founder proposing a new venture.

A startup founder's perception of time plays a compelling role in decisions such as what ideas are pursued, what types of markets are explored, what type of deadlines are adhered too and many other important choices made in the life of a startup. These in turn play a crucial role in the performance of the venture. To understand the perception of time better we can study the extent to which individuals devote attention to perceptions of past, present and future. This can be described by an individual difference construct, namely temporal focus (Bluedorn & Martin, 2008; Shipp, Edwards, & Lambert, 2009). Temporal focus is very relevant for startup founders because past knowledge and experiences, real-time information, and future speculations are all considered to be important in strategic decision-making (Nadkarni & Chen, 2014). Future focus concerns with thinking about only what the future holds and contemplating future events. The way we imagine our future can play an important role in decision-making. Strategic decision-makers, and in particular startup-founders, aim at shaping the future, dealing with "cognitively distant" opportunities (Gavetti, 2011, page 120). They have to construct those opportunities not only in their own minds, but they also have to persuade and mobilize others (Gavetti, 2011, 2012). How they construct those distant opportunities is an important matter. According to a solid theory in psychology, the future can be construed in either abstract or concrete ways (Liberman & Trope, 1998; Trope & Liberman, 2003; Trope, Liberman, & Wakslak, 2007). This dimension can play a significant role in planning implementation and executions of tasks and goals and thus significantly influence startup founder's success.

Therefore, it seems important to not only understand how future temporal focus affects performance, but also to delve deeper and disentangle whether different ways of construing the future might affect performance.

We extend our exploration of differences in temporal focus of startup founders, by looking at how startup founders categorize themselves in these temporal spaces. We focus on two dimensions namely personal categorization, and collective categorization where we look at how identity is construed in relationship or distinguished from others. In addition, how startup founders perceive themselves as either individualistic or collectivistic impacts various choices such as the type of team a person works with or the way a business plan is written. These differences also directly affect team climate and cohesion, which are known to directly affect performance. These differences have known to play a role in effectiveness of leaders, and we postulate that these will hold true for startup founders.

Authors in the behavioral theory of strategy (Gavetti et al., 2012), have made a call asking for uncovering the central antecedents that could explain heterogeneity across firms performance. In such effort, we propose and empirically test the relationships between central antecedents perception of time and self to the performance of startups at multiple levels. We do so by testing the relationships between self-categorization, temporal focus, construal level constructs with performance of startups. We find that individual differences in past focus, future focus, future construal and self construal play a key role in determining performance and thus we contribute in extending micro foundations research in strategy (Gavetti et al., 2012). We extend these findings and test them on a team level and find that the results mirror the individual level results and team diversity in the above dimensions does not play a role in determining performance.

THEORY DEVELOPMENT

Different temporal focuses are associated to different decision-making styles (Shipp et al., 2009). Bryant, Smart, and King (2005) show how certain individuals tend to reminisce less about the past than others. These differences could influence how present decisions are made under uncertainty and in turn, could affect organizational outcomes.

Yadav and colleagues' study was one of the first to show how the time to which organizational leaders pay attention influences organizational innovation outcomes. Yadav et al. (2007) used stakeholders' reports to analyze how inter-individual differences in the temporal focus of CEOs correlate to their organizations' innovation outcomes. In particular, the authors measure variables related to how quickly organizations detect new technological opportunities, develop initial products based on these technological opportunities, and deploy these new products. The authors find a positive correlation between the amount of attention individuals' pay to the future and the innovativeness of their organizations.

Related to Yadav and colleagues' (2007), Bluedorn (2002) published a study on entrepreneurs' perceptions of time, in particular perceptions of temporal depth. The authors found that perceptions of past and future depth are positively related. Entrepreneurs' temporal depth perception is associated with variables that affect the management of the organizations they lead, including their ability to plan, follow a schedule and meet deadlines, the pace of their work, and their punctuality, among other things. Bluedorn and Martin measure these variables using a survey method, and using the same survey they measure entrepreneurs' temporal depth using the

Temporal Depth Index, which measures past and future, but not perception of the present Bluedorn and Martin (2008).

More recently Nadkarni and Chen (2014) found that temporal focus of CEO’s interacts with environmental dynamism to predict the company’s rate of new product introduction (NPI). They focused on 221 large manufacturing firms and found that depending if the environment was stable or dynamic, CEO’s temporal focus predicted the rate of NPI. They triangulated their findings by relying on various secondary data sources such as letter to stakeholders and interviews to the press.

These studies highlight that there are important inter-individual differences in the time individuals focus their attention on. The interesting implication for the management field is that inter-individual differences in temporal focus and perception are associated with the development of the organizations led by such individuals.

The limitation of these studies, which is acknowledged by their authors, is that they do not rely on direct measures of the actual temporal focus individuals are paying attention to, but rather the temporal focus they report to third parties (i.e. stakeholders reports in Yadav et al.’s study (2014), and the time depth reported in the questionnaire (i.e. the self-reported index in Bluedorn and Martin’s study (2007)). While the focus and perception of time could be self-reported based on responses to a survey question asking respondents to reflect on their behaviors, it is necessary to complement these measures using methods that allow individuals to behave spontaneously recording their thoughts in real time. In addition, rather than relying on a single report, it would be optimal to obtain finer grained data obtained through multiple data points of each individual to complement this information. This would allow reliance on data that are more representative of single individuals, and not data that characterize their state at a single point in time.

The informal and immediate nature of conversational content makes the content closer to the author's cognitive processes and spontaneous views. This makes Twitter a useful source of individual perceptions of ongoing events. Fischer and Reuber's study (2011) confirms that Twitter data are a reliable source of entrepreneurs' spontaneous thinking. Should the entrepreneur be a particularly avid Twitter user, and then these Tweets will be a source of abundant and fine-grained longitudinal data on their thinking.

Fischer and Reuber (2011) proposed that Twitter constitutes an important platform for understanding entrepreneurs' cognitive processes. Based on interviews on the use of Twitter and other social media, the author's find that entrepreneurs express their thoughts and interact with others using Twitter. The entrepreneurs in Fischer and Reuber's study prefer Twitter than other social media (e.g. Facebook). Importantly, the entrepreneurs in the study report "Tweeting" in the same way as they would approach a conversation, and feel they have freedom to share their "thoughts" and "voice" with those who follow them or their companies (2008).

Twitter has been used in research on a range of topics. For example, individuals Tweets have been used to gauge the mood of the stock market (Bollen, Mao, & Zeng, 2011), to manage crises in organizations (Schultz, Utz, & Göritz, 2011), to predict election results (Tumasjan, Sprenger, Sandner, & Welpe, 2010), and to measure users' views of an organization (Tan et al., 2011).

We use Twitter data to collect startup founder's thoughts over time. We then analyze inter-individual differences in the expressed in their thoughts, and correlate those differences with the performance of their startups.

Archival data capturing written thoughts of individuals has been validated and used to capture an individual's perception of time (Nadkarni & Chen 2014, Yadav et al., 2007). Hence, analysis of entrepreneurs' Tweets can provide a direct measure of the temporal focus to which entrepreneurs are paying attention. Also, Twitter data are generally spontaneous - although Twitter users might filter it to an extent, it is most decisively less filtered than, for example, stakeholders' reports. Twitter data are available over time, making possible multiple observations for each individual.

By building on studies from psychology and strategy, we depend on temporal focus, construal level theory and self-categorization to explain performance differences in startups. Our objective is to understand whether startup founders differ in the temporal focuses, construals and self-categorizations adopted and how inter-individual differences are related to performance outcomes relation between a certain temporal focus and achievement of better performance? To further validate our results we test our hypotheses at the team level.

HYPOTHESES

Temporal focus

In our study we are interested in understanding how differences in temporal focus relate to startup performance. Temporal focus can be defined as the attention individuals devote to the past, present, and future (Shipp 2009). This concept is very important because it affects how people incorporate into their mental processes their perceptions about past experiences, current situations, and very importantly for us, their anticipation of future expectations into their attitudes, cognitions, and finally into their behavior. The behavioral theory of the firm and the neo-Carnegie School have emphasized the importance of understanding decision-makers' attention (Cyert & March, 1963; Ocasio, 1997, 2011), and temporal focus is a pivotal concept in advancing our understanding of how decision-makers notice, encode, and interpret both the issues and answers that surround them (Ocasio, 1997, page 189). Temporal focus describes the extent to which people characteristically devote their attention to perceptions of the past, present, and future (Bluedorn, 2002; Shipp et al., 2009).

Temporal focus is one component of an individual's broader time perspective (Berends & Antonacopoulou, 2014). Lewin (1951) defined time perspective (TP) as "the totality of the individual's views of his psychological future and psychological past existing at a given time" (Lewin, 1951, page 75). Time perspective of entrepreneurs has been studied in conjecture with risk behavior or growth facilitation (Das & Teng, 1997; Fischer, Reuber, Hababou, Johnson, & Lee, 1997). And the central findings of this body of literature are that risk horizon and time horizon are intertwined.

Another related concept is temporal depth. Temporal depth can be distinguished from temporal focus, as the first is related to the horizon one looks into in the past or future. For example, an individual can have a very high future horizon, but this does not preclude them from having a high present focus. Works by Shipp and colleagues (2009) have shown that temporal focus and temporal depth are independent and measure different aspects of time perspective. Temporal focus captures the present dimension, which is ignored in temporal depth. Very importantly, temporal focus has also been shown to be a trait-like construct, that is, it stable over time among individuals

Our objective is to understand whether startup founders differ in the temporal focuses adopted and how inter-individual differences are related to performance outcomes. Yadav et al.'s (2007) study of CEOs show that those executives with higher future focus lead more innovative organizations. Does this apply also to the case of entrepreneurs? Bluedorn and Martin (2008) find that the depth of past and future focus is positively related to variables important for the management of startups, such as the ability to adhere to plans and meet deadlines. Can we also expect a positive relation between a certain temporal focus and achievement of better performance?

Past experience and understanding of the past create a backdrop against which present actions leading to the future are taken. For a startup this implies temporal resources must be acquired and allocated which in turn affects the type of options exploited, the pacing of various activities and finally the emergent organization culture (Bird & West, 2007). Past focus can enhance learning through analysis of previous actions and rumination of mistakes and regrets (Holman & Silver, 1998). For instance the concept of retrospective sensemaking is about drawing upon past knowledge to use in current situations (Bluedorn, 2002; Weick, 1995).. Thus a high past focus can be extremely fruitful to a startup founder as this will help in gaining a deeper understanding of his environment and will facilitate faster detection of new opportunities. Based on this we expect that high past focus can translate to higher learning and sensemaking and thus result in a superior performance.

Hypothesis 1a. The higher the past focus of a start up founder, the more funding that startup founder raises.

A strong present focus can help startup founders with an updated view of their current environment, thus better enabling them to detect new technological and market opportunities (Nadkarni & Chen, 2014). Individuals with strong present focus pay more attention to the here and now, and usually have a higher sense of well being. The downside of a strong present focus is that it can lead to impulsive behaviors, unwarranted risk taking and inattention to the consequences of current behaviors (Zimbardo & Boyd, 1999; Zimbardo, Keough, & Boyd, 1997). For startup founders, not heeding to consequences of current behaviors can be detrimental in the long term. This can translate to lesser funding raised than those who founders who are not only high in present focus. Hence we expect that a high present focus can be unfavorable for high performance.

Hypothesis 1b. The higher the present focus of a start up founder, the less funding that startup founder raises.

Individuals high in future focus are usually high in motivation and ambition. This can impede well being by creating anxiety (Shipp et al., 2009). For start-ups founders, if they were to divert their efforts to yet to occur technologies, markets or services they could be exhausting resources that might be needed for their current venture. Yadav et al. (2007) demonstrated that CEO's with high future focus emphasize on futuristic technologies that are ill understood. This can also lead to startup founders spending a lot of time planning and developing future scenarios but not committing to or deploying anything. Thus we expect high future focus of start up founders to be pernicious to performance for startups.

Hypothesis 1c. The higher the future focus of a start up founder, the less funding that startup founder raises.

Self-categorization

Understanding how individuals represent themselves and how that relates to time is poorly understood. Research in psychology has focused a lot on the individual self-concept, i.e. the person's unique sense of identity differentiated from others. Works following have shown an interest in how individuals define themselves in relation to others (Markus & Kitayama, 1991). Brewer and Gardner (1996) point out that how individuals identify themselves entails fundamental differences in the way the self is construed. Collective categorization (e.g. we believe), consistent with the social identity perspective, is known to foster well-being, improve team cohesion and team climate whereas personal categorization (e.g. I believe) could increase conflict and tensions within a startup. On a separate but related research stream, higher team cohesion has been linked to better performance (Evans & Dion, 1991). Edmondson and

Nembhard (2009) emphasize the role of interpersonal conditions for teamwork. As uncertain environments come with a high risk of failure, good interpersonal relationships become a priority for success. Lower team cohesion can result in communication failures due to tensions among team members and this affects the ability to report and correct mistakes which in turn lead to poor performance (Edmondson, 1996). Research has not focused on comparing individuals and collective levels of self-categorization. We want to better understand whether self-categorization can impact performance. To do so we focus on how much the startup founder focuses on her or him self-categorization versus on a collective categorization. Based on the above reasoning, we expect to see collective self-categorization fostering performance and personal self-categorization hindering startup performance.

Hypothesis 2a. The higher the personal self-categorization of a start up founder, the less funding that startup founder raises.

Hypothesis 2b. The higher the collective self-categorization of a start up founder, the more funding that startup founder raises.

Team Level

Finally we would like to extend our findings from the individual level to understand the team level. Our objective is to understand what relationship have our variables of interest - high past focus, low future and present focus, higher collective categorization and lower personal categorization- with the performance of the startup when taking into consideration not only one single founder, but the entire team of founders. Our implicit assumption is that the effects that took place at the individual level of analysis should add up and therefore that all of our variables of interest should be positively associated with startup performance.

In addition, we want to understand diversity. Mohammed and Nadkarni (2011) found research surrounding temporal diversity to be inconsistent. Research exploring team diversity on a temporal level has claimed that there is “lack of clarity surrounding when heterogeneity vs. homogeneity is valuable”. On one hand higher temporal diversity can contribute to different dimensions being focused on and different tasks being catered to, on the other hand temporal diversity can create ambiguity about tasks deadlines, priorities and create tensions and dissatisfaction among team members (McGrath, 1991). Similarly diversity in self-categorization can create conflicts but also foster different identities and roles within a company. We choose to control for diversity, as it can also be an important determinant of startup performance.

METHODS

Sample

Our data relies on the database Crunchbase a public domain database. Crunchbase began as a simple crowd sourced database to track startups on TechCrunch and now claims to have more than 50,000 active contributors. Members of the public, subject to registration, can make submissions to the database; however, all changes are subject to review by a moderator before being accepted. Editors to ensure it is up to date constantly review data. Crunchbase says it has 2 million users accessing its database each month. Now they boast more than 650k profiles of people and companies that are maintained by many contributors and moderators.

This database gives us a complete overview of VC funding for many startups. The website contains longitudinal data about start-up firms, entrepreneurs, and investors including their funding histories, founding teams. Databases such as Crunchbase, Zoominfo are steadily gaining reputation among strategy researchers (Arora & Nandkumar, 2012). In particular, Crunchbase has been used in previous studies The studies show that Crunchbase data correlates well with VC data from other sources such as US National venture capital program (Alexy, Block, Sandner, & Ter Wal, 2012; Block & Sandner, 2009).

In order to allow for homogeneity in the environment (which has proven to cause many differences in temporal perspective, see work by Levine (2008), and to select for an environment where many startups are founded, we focused on startups in the SF bay area. SF bay area in 2013 received 46% of all nationwide venture capital funding in USA (Delevett, 2013). In 2002, a study by USA Today asked the USA TODAY asked the National Venture Capital Association to rank the top 10 cities for start-ups, San Francisco and the bay area came on top of the list, as the number 1 area in the US to fund a startup (Graham, 2012). Main reasons are the availability of talent and relatively low costs, and the possibilities to raise money (Graham, 2012). For these reasons we focused on the SF bay area to collect our sample of entrepreneurs. We downloaded the data on 6th June 2014 from the Crunchbase excel exports (Crunchbase, 2014). We focused on organizations that were founded after March 2006, which is the date

Twitter, was founded (Arceneaux & Weiss, 2010). For each of these startups, we collected a list of their founders, date founded, funding raised, funding rounds and markets they catered to. We excluded variables, which contained missing data and those ventures, which had not disclosed funding, and our sample contained 1433 startups. The startups on average had raised 14.3 million $ or had a median of 3 million $ and an average of 2.3 founders per startup.

Our regression analysis is conducted on this reduced sample. This implies our analysis and conclusions will reflect the structure of this sample and can be potentially limited to the SF bay area.

Data source for startup founder temporal focus

Nadkarni and Chen (2014) have pointed out that it is not easy to find reliable sources to measure temporal focus. They point out how surveys and interviews can result in low response rates and result in biases due to social desirability, reactivity etc. Berends and Antonacopoulou (2014), claim that studying temporal variables is extremely difficult as inquiry relying on retrospection alone is not a good measure as it is retrospection that is at stake.

Twitter data, which is otherwise known as Microblogging can overcome most of the issues encountered in survey research (Java, Song, Finin, & Tseng, 2007). Websites such as *Facebook, tumblr and Twitter* are where millions of messages are exchanged daily. Due to its easy accessibility and free format of messages (unlike traditional blogs or mailing lists) we see more internet users using microblogging services (Pak & Paroubek, 2010). Typically authors of microblogs write about their life, share opinions on variety of topics and discuss current issues (Pak & Paroubek, 2010).

Thus for every organizations in our dataset located in the San Francisco bay area of USA, we collected publicly available Twitter data related to the startup company account and the founder's personal account. In total, we found 2880 founder accounts from which around 80 % had personal Twitter accounts. Due to restrictions from the Twitter API we were able to collect a maximum of 3200 tweets per person. In addition we were able to obtain the total number of tweets tweeted by this person which is controlled for in later analysis.

Measures and controls

Dependent variable

Crunchbase is a web-based platform that mostly attracts innovative startups that want to gain funding and use this platform as a window to showcase their ideas and gain visibility among potential capital investors (Crunchbase, 2014). For each of the startups in Crunchbase the total funding raised is known and it can go from zero to several millions. Funding can be obtained through venture funding, angel investors, seed investors, private equity, grants debt financing, equity crowd funding or a combination. We measure startup performance by the total amount of funding raised. To carry out individual level analysis we run analyses with both the total funding and also we divided the total funding by the number of founders. Interestingly, our results were similar when carried out with both funding raised and funding raised divided by the number of founders. For the sake of brevity we only report the results of total funding raised. For the team level analysis we look at the total funding raised as our dependent variable.

Individual measures: Independent variables

In order to analyze these data to obtain representative values for temporal focus, we used a robust and well established psycholinguistic tool for coding Twitter data namely the Linguistic Inquiry and Word Count (LIWC)(Tausczik & Pennebaker, 2010). This tool exists in several languages and has been refined using data collected over 25 years. It codes across different cognitive and emotional categories and is available in over 70 languages. The LIWC software calculates the extent to which certain cognitions and emotions are present in the text. For each of these dimensions, a frequency based on words which are related to a category for instance future focus would includes words such as will, may, going to etc. It is important to note that words are counted and then normalized by the length of the text so all reported measures are in proportion to the total amount of tweets we analyze. This prevents our measures from being distorted by the frequency or length with which a person tweets. LIWC has been regularly in psychology and linguistics where it is considered a reliable tool (see (Tausczik & Pennebaker, 2010)).

Recent works by Nadkarni and Chen (2014) relied on the categories in LIWC to code CEO'S temporal focus. They found high reliability of LIWC across different sources of text for measuring temporal focus and also demonstrated very strong convergent and discriminant validity for temporal measures using LIWC in a validation study. Based on these works we relied on LIWC to measure our various variables of interest.

One of the primary aims of our study is to analyze how startup founders converse rather than what the content of the conversation is. Thus in our Twitter data, we excluded retweets, #hastags and @mentions to include only data which is written by the founder. IBM researchers found 250 tweets to be enough to derive personality profiles along 52 different personality traits, they found excellent correlations with psychometric tests and using larger amounts of tweets (Takahashi, 2013). Nadkarni and Chen (2014) found that a three-page student essay was enough to correlate very highly with the temporal focus questionnaire. Hence we excluded Twitter accounts, which contained less than 2000 words. We did so, to have a minimum quantity of words that past studies have been considered more than enough to measure entrepreneurial sentiments. We also ignored accounts, which had not disclosed funding raised. In the end we had 2111 startup founders who met the above criteria.

In order to measure entrepreneurial sentiment we focus on 7 dimensions. These dimensions are future focus, past focus, present focus, HLC[*], LLC[1], personal categorization and collective categorization. Table 1 illustrates examples of tweets for each categories and table 2 describes each of the variables, additionally in the appendix in table A1 we list some examples of words, which are included by LIWC for each of these categories.

Controls

[*] For HLC and LLC, we only counted words in sentences that included an at least one future focus word.

We control for sector, by obtaining the markets from the Crunchbase database and obtaining SIC codes for each of the startups. We control for the first digit of the SIC code for each startup, separate analysis with the all digits indicate similar results and have not been reported for the sake of brevity. We control for the year the startup was founded as this can have a significant influence in the amount of funding raised. We also check if number of founders in founding team plays a role in funding raised. In addition to analyzing a maximum of 3200 tweets per individual, we also control for the total number of tweets by each startup founder. Two other controls are the status of the startup if it is still operating (0) or has been acquired (1) and how much each startup founder refers to words related to time such as early, evening, summer, due etc. which are also coded using LIWC.

To code for gender for every individual we matched his or her first name in a machine learning gender classifier (Genderize.io, 2014). By matching with big data sets of information such US Social security database or social network data it matches with approximately 190558 names and also produces a certainty value. This method has been previously used for names on Twitter (Mislove, Lehmann, Ahn, Onnela, & Rosenquist, 2011), authors of research papers (Sugimoto, 2013) and much recently in management for coding names of IBM engineers (Dahlander, O'Mahony, & Gann, 2014).

We ran a separate analysis with 1700 entrepreneurs in our study and found that age was not correlated to the study variables and did not change the regression results. For the sake of brevity we do not report in the results.

INSERT TABLE 1 ABOUT HERE

INSERT TABLE 2 ABOUT HERE

Team level variables:

For startups with 2 or more founders (N=620), we used averages of the independent variables in table 4 for each startup to calculate team level temporal focus and self- categorization. Using the standard deviation we calculated the diversity along these dimensions.

RESULTS

Table 3 and 4 illustrate the descriptive statistics for the variables at the individual and team level. Our data represents 1433 firms and 2111 founders.

INSERT TABLE 3 ABOUT HERE

INSERT TABLE 4 ABOUT HERE

We use a logarithmic transformation on our dependent variable funding to make the analysis more suitable for linear regression. We then test the effects of temporal focus, categorization and construals on the logarithm of funding raised.

For our regression analysis we calculated the value inflation factors (VIFs) for all combination of variables and found that all VIFs are below 2, which is below the accepted limit of 10.0 (Kutner, Nachtsheim, & Neter, 2004). This indicates that multicollinearity is unlikely to be a concern in our analyses.

In table 5 model 1, we included only the controls, in model 2 we include temporal focus and categorization. H1a proposed that higher startup founder past focus will relate positively to funding raised, as shown in table 5, past focus is significant and positive ($B = 0.214$, $p < .001$). We do not find support for H1b, as the effect present focus is not significant. H1c predicts that future focus will be negatively related to startup funding raised. The results support this finding ($B = - 0.289$, $p < .05$) and suggest that it is important look backwards to move the startup capital forward.

We see strong support for hypothesis 2b, which states that higher collective self-categorization of a start up, is associated with higher funding raised (B = 59.896, $p < .001$), 2b is supported at the 10% level and high personal self categorization is associated with lower funding raised. By including the temporal and categorization variables we are also able to explain more about the funding raised as the adjusted R^2 increases by 3% compared to model 1 with only controls.

Further analysis: Unpacking future focus

To better understand how future focus impacts performance. We unpack the future focus proposes that individuals construe mental events differently. Given that individuals can only experience the here and now, we transcend and perceive distal entities by forming mental construals of distal objects. Typically, as an event becomes removed from one's direct experience, detailed information about it becomes less reliable or available (Fujita, 2008; Liberman & Trope, 1998; Trope & Liberman, 2003; Trope et al., 2007).

An extensive literature has supported the notion that people construe events differently as a function of psychological distance, even when equivalent information is available (Liberman & Trope, 1998; Trope et al., 2007; Wakslak, Nussbaum, Liberman, & Trope, 2008; Wakslak, Trope, Liberman, & Alony, 2006). Depending on their goals, different construals are used. In particular, individuals can construe future events in a higher-level construal (HLC) thus forming abstract representations or low level construals (LLC), which are more concrete and specific.

Research has suggested that there are individual differences in the chronic tendency to construe events at high- versus low-levels (e.g., Freitas, Salovey, & Liberman, 2001; Fujita, 2008; Levy, Freitas, & Salovey, 2002; Vallacher & Wegner, 1989). What is important to note is that people utilize their mental capacity to understand their environment and express themselves at differing levels of abstraction, and that these differences in their construals subsequently impact judgments, decisions not only of themselves but of those that surround them.

Startup founders' live in a world of opportunities. In particular, as proposed by Gavetti (2011), they have to deal with "cognitively distant" opportunities and events. The more those individuals will make their world appear concrete (low level construals (LLC)), the more they will succeed at act on those opportunities, and also mobilize others to follow them.

We do not see support that abstract thinking influences startup performance as shown in Model 3 in Table 5, i.e. the more abstract the startup founder is while referring to the future the less funding the founder raises. But we do see support for concrete future focus, which is a lower level construal plays a role in attracting more funding ($B = 0.121$, $p < .05$).

INSERT TABLE 5 ABOUT HERE

The team level results are shown in table 6, model 1 represents the regressions with only the controls; model 2 with the diversity of the study variables per team as controls and model 3 includes the mean of the study variables per team as well. The results in model 3 are very similar to the findings at the individual level. As illustrated in model 3 in table 6, we see that means of past focus, collective categorization and LLC are all positively associated with funding raised. Surprisingly as shown in model 2 we do not find support for diversity along our study variables contributing to funding raised. We are also not able to explain our dependent variable better with the addition of these new variables, as the adjusted R2 change is .002 from model 1.

INSERT TABLE 6 ABOUT HERE

DISCUSSION

Our study contributes to the strategy literature by connecting psychological constructs to venture performance. We answer calls from the behavioral theory of strategy (Gavetti et al., 2012), and uncover antecedents which explain performance heterogeneity in new ventures. With relying on the latest data sources, we study attention given to perception of time and self that would be difficult to obtain through self reported measures. We rely on solid theories from psychology and use Twitter data to measure temporal focus, level of construal and self-categorization in a sample of startup founders. We use those measures of the startup founders to predict their startup performance. We find high past focus, low future focus, high collective self-categorization and lower level construal to be associated with better performance. These results hold true not only at the individual level of analysis, but also at the team level, and demonstrate the importance of perceptional biases in new venture performance.

Methodologically we contribute by using novel data sources such as Twitter and Crunchbase, which have gained enormous importance not only as general media, but also as social platforms for exchanging business-related information. The combination of these data sources and dictionary tool lend themselves to analyze fine-grained variables that were previously not possible to measure in such precise ways.

Our results have some limitations. Firstly, while the CrunchBase data has several advantages described in the methods section, its use, in conjunction with Twitter data, limits our generalizability and limits the amount of variables we can control for. In terms of generalizability, we could only extend to startups and founders who are technologically savvy and typically tend to be between the age groups of 15 to 50 years. Also, like Nadkarni et al. (2014) we do not control for the environment's uncertainty, this could interact with various individual level constructs to influence funding raised. In our results we find future focus to be negatively related with performance. It could be that this result is due to the fact that startup founders in the SF bay area have a higher future focus than the rest of the population. We are currently analyzing a comparative sample with individuals from the rest of the world. This additional sample will constitute a control group to compare and further investigate our results. If this paper submission is accepted, we will present the comparative results during the conference.

Future research can explore the role of the environment of a startup and these individual level variables. Our results focus on the SF Bay area, known to have a high density of startups. Whether these results are a feature of the environment could be tested in future research by including other locations and countries.

Albeit preliminary, our results have several managerial implications. In line with Fischer and Reuber (2014), our findings could help entrepreneurs who either use or consider using social media to communicate in ways that would make their startups more appealing to both their teams and potential investors.

First of all, our results not only point to the importance –nowadays pervasive- of social media in the entrepreneurial context, but more precisely, point to the impact that individual temporal focus and categorization have on venture performance. Startup founders are constantly accumulating and filtering information and paying attention to others, making future projections, and categorizing themselves and others. Our results support that startup founders who rely on past knowledge and have a high past focus can contribute positively to funding raised, whereas those who are high in future focus might envision several futures but might fail to implement any one of them. Importantly though, in this research we zoom into temporal focus by looking at how the future is referred to, and how the self is categorized. These two dimensions had not been previously connected to entrepreneurial performance. In addition, looking at these variables in our setting of social media is timely and provides with an opportunity to derive managerial implications as entrepreneurs reflect on their use of this sort of communication channels. Since our findings show that startup founders who think about the future in more certain terms tend to do better in their ventures, entrepreneurs could make an effort to report and express their ideas about the future in more concrete terms. In other words, it seems that it is important to look backwards to move forward with concrete steps.

Interestingly, in our study team level temporal diversity does not seem to play a role directly in startup performance. It might interact or mediate with other variables, which are not accounted in the study. Finally, and very interestingly, our results show that how startup founders categorize themselves has a significant impact on funding raised. Founders, who use more collective categorization, with words such as we and ours, are promoting a more holistic and inclusive environment that might foster better relationships with colleagues and investors. Entrepreneurship promotion programs, learning spaces, coaching, and training sessions could help startup founders to reflect on their past and zoom into the future and try to add more details to abstract visions, while actively and collectively engaging others as action agents.

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TABLES AND FIGURES

Table 1: Example of tweets per construct

Construct	Example tweet
Past focus	Today was a good day of working out mind and body. Rhythm is wonderful.
Present focus	Love debating how tech & education can bridge the gap in economic opportunity.
Future focus	As mobile makes us more mobile, people will shift between countries more often
Collective categorization	In the end, we are our choices.
Personal categorization	**I** need to figure out how to go work at @spacex **I** can't believe how @elonmusk is making the future real! http://t.co/ICl3hM9JVR
HLC	Data **perhaps** the most valuable asset of legal blog networks - RLHB http://t.co/yHLCyqqCqX h/t @jeffjohnroberts
LLC	After a few days with it, I'm **certain** that @brackets is the right choice for @missionbit students this semester. Makes HTML & CSS more fun!

Table 2: Summary of variables at individual level of analysis

Variable	Description	Source
Controls		
Founding year	2006-2013	Crunchbase
Sector	First digits of the four digit SIC code (1-9). The SIC	Crunchbase analysis
Gender	Male or female (0,1)	Gender Classifier
Status	Operating or acquired (0,1)	Crunchbase
Nfounders	No of startup founders	Crunchbase
Nalltweets	No of total tweets made by the startup founder	Twitter data
Time	Count of time related words detected by LIWC/ Total words detected by LIWC	LIWC analysis
Independent variable		
Future focus	Count of future words detected by LIWC/ Total words detected by LIWC	LIWC analysis
Present focus	Count of past words detected by LIWC/ Total words detected by LIWC	LIWC analysis
Past focus	Count of present words detected by LIWC/ Total words detected by LIWC	LIWC analysis
HLC	Count of tentative words detected by LIWC for future focus sentences/ Total words detected by LIWC for future focus sentences	LIWC analysis
LLC	Count of certain words detected by LIWC for future focus sentences/ Total words detected by LIWC for future focus sentences	LIWC analysis
Personal self-categorization	Count of 1st person singular words detected by LIWC/ Total words detected by LIWC	LIWC analysis
Collective self-categorization	Count of 1st person plural words detected by LIWC/ Total words detected by LIWC	LIWC analysis
Dependent variable		
Funding_raised	Log (Total funding raised by startup)	Crunchbase

Table 3: Descriptive Statistics and Correlations among all individual level variables[a]

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	Controls																	
1	Founding year	2010.32	1.85	1														
2	Gender	0.10	0.31	.07**	1													
3	Sector	6.04	2.08	.05*	-.05*	1												
4	No. of founders	2.36	0.96	-.06*	-.05*	0.00	1											
5	No. of tweets	3376.70	6031.29	0.01	0.01	-.06*	-0.008	1										
6	Status	3.27	1.18	.15**	.06*	0.02	-0.018	0.01	1									
7	Time focus	0.08	0.01	0.01	0.00	-0.02	.050*	-.09**	-0.02	1								
	Study variables																	
8	Past focus	2.46	0.78	0	-0.02	-.10**	.079**	.05*	-.06**	.19**	1							
9	Present focus	10.85	1.79	.05*	.07**	0.01	.067**	.10**	0.01	-.14**	.22**	1						
10	Future focus	1.15	0.35	0.01	-.04*	.06**	0.035	.07**	0.04	-.10**	.13**	.37**	1					
11	HLC	3.41	1.05	-0.02	-0.01	-0.04	.055*	.11**	-0.04	-0.04	.26**	.22**	.15**	1				
12	LLC	1.52	0.67	0.03	0.02	-0.03	0.038	.05*	-0.04	-.05*	-0.02	0.00	-.10**	0.00	1			
13	Personal categorization	0.04	0.02	.09**	.06*	-.05*	.096**	.06**	-0.03	.17**	.58**	.44**	.13**	.20**	-0.03	1		
14	Collective categorization	0.01	0.01	-.07**	.07**	.06**	-0.003	-0.01	-0.01	-.10**	-.16**	.19**	.19**	-.14**	-.10**	-.20**	1	
15	Log (funding raised)	14.83	1.95	-.35**	-.05*	0.03	.100**	-0.04	-.07**	-.09**	-0.01	-0.02	-0.01	-0.04	0.02	-.10**	.19**	1

[a] N=2111 startup founders

* p < .05. **p < .01. ***p < .001.

Table 4: Descriptive Statistics and Correlations among all team level variables[a]

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	Controls																	
1	Team_Founding year	2010.27	1.80	1														
2	Team_Gender	0.11	0.22	0.06	1													
3	Team_Sector	5.89	2.17	.08*	-0.05	1												
4	Team_No. of founders	2.64	0.78	-.10*	-0.02	-0.04	1											
5	Team_No. of tweets	3678.66	4493.82	-0.04	0.04	-.11**	-0.02	1										
6	Team_Status	3.23	1.17	-.32**	-0.05	-.08*	0.02	0.06	1									
7	Team_Time focus	7.64	0.93	-0.09	0.04	0.00	.10*	-.09*	.08*	1								
	Study variables																	
8	Team_Past focus	1.16	0.25	-0.05	0.04	-.12**	0.04	.16**	.20**	.18**	1							
9	Team_Present focus	2.51	0.62	0.01	0.08	0.04	0.03	.19**	0.03	-.12**	.25**	1						
10	Team_Future focus	10.96	1.33	0.02	-.10*	0.05	0.04	.14**	-0.04	-.09*	.10*	.50**	1					
11	Team_HLC	3.46	0.75	-0.04	-0.05	0.014	0.05	.14**	.11**	-0.00	.33**	.26**	.19**	1				
12	Team_LLC	1.57	0.47	.09*	0.02	-0.03	-0.03	0.03	0.01	-0.06	-0.06	-.12**	-.17**	-0.041	1			
13	Team_Personal categorization	3.92	1.20	.09*	.12**	-.09*	0.07	.14**	.16**	.20**	.61**	.47**	.11**	.246**	-.08*	1		
14	Team_Collective categorization	1.11	0.43	-0.03	0.04	.09*	-0.00	-0.02	-0.03	-.10*	-.17**	.27**	.25**	-.153**	-.13**	-.16**	1	
15	Team_Log (funding raised)	14.79	1.94	-0.28**	-0.07	0.04	.11**	-0.05	-0.03	-.10*	0.01	0.00	-0.02	-0.052	0.03	-.11**	.23**	1

[a] N=620 startup teams

*p < .05. **p < .01. ***p < .001.

Table 5: Results of regression analysis at individual level for relationship between temporal focus, construals and categorization with startup performance[a]

Independent variables	Model 1	Model 2	Model 3
Control variables			
Founding year	-0.386***	-0.365***	-0.367***
Gender	-0.113	-0.173	-0.176
Sector 1	0.073	0.086	0.06
Sector 2	-0.303**	-0.294**	-0.295**
Sector 3	0.213	0.227	0.318
Sector 4	-0.752**	-0.76**	-0.754**
Sector 5	-0.645**	-0.662**	-0.654**
Sector 6	0.658***	0.655***	0.649***
Sector 8	0	0.007	0.008
Sector 9	0.126	0.043	0.025
No. of founders	0.171***	0.177***	0.171***
No. of tweets	-0.00001193	-9.92E-06	-1.02E-05
Status	-0.349**	-0.339**	-0.344**
Time focus	-13.63***	-13.41***	-14.597***
Study variables			
Past focus		0.215***	0.222***
Present focus		-0.023	-0.033
Future focus		-0.289*	-0.259*
Personal categorization		-6.216	-5.474
Collective categorization		59.896***	59.805***
HLC			-0.045
LLC			0.121*
Adjusted R^2	0.154	0.185	0.189
Change in R^2		0.031	0.004

[a] Coefficients are reported; n = 2111 startup founders

*p < .05. **p < .01. ***p < .001.

Table 6: Results of regression analysis at team level for relationship between temporal focus, construals and categorization with startup performance [a]

Independent variables	**Model 1**	**Model 2**	**Model 3**
Control variables			
Founding year	-0.35***	-0.353***	-0.337***
Team_Gender	-0.23	-0.223	-0.383
Sector 1	0.584	0.525	0.319
Sector 2	-0.15	-0.114	-0.135
Sector 3	0.827	0.81	0.932
Sector 4	-0.886	-0.905	-0.908
Sector 5	-0.667	-0.662	-0.588
Sector 6	0.767	0.724	0.672
Sector 8	0.24	0.233	0.279
Sector 9	0.202	0.104	-0.024
No. of founders	0.203*	0.192	0.236*
Team_No. of tweets	0*	0*	0*
Status	-0.496*	-0.488*	-0.545*
Team_Time focus	-0.24**	-0.24**	-0.204*
Team controls: Diversity variables			
Diversity_Pastfocus		0.225	0.088*
Diversity_Present focus		-0.057	-0.05
Diversity_Future focus		-0.261	-0.236
Diversity_Personal categorization		-0.066	0.083
Diversity_Collective categorization		0.412	-0.356
Diversity_HLC		-0.07	-0.073
Diversity_LLC		-0.061	-0.268
Study variables			
Team_Past focus			0.5**
Team_Present focus			-0.034
Team_Future focus			-0.448
Team_Personal categorization			-0.153
Team_Collective categorization			1.309***
Team_HLC			-0.066
Team_LLC			0.479*
Adjusted R^2	0.116	0.118	0.176
Change in R^2		0.002	0.058

[a] Coefficients are reported; n = 620 startup teams

*p < .05. **p < .01. ***p < .001.

APPENDIX

Table A1: Examples of LIWC words per construct

Construct	Example word 1	Example word 2	Example word 3	Total number of words in category
Past focus	accepted	admitted	affected	145
Present focus	admit	admits	aint	169
Future focus	couldve	could've	gonna	48
Personal categorization	i	Id	I'd	12
Collective categorization	lets	let's	our	12
HLC	allot	almost	alot	156
LLC	absolute	absolutely	accurate	83
Time focus	abrupt	after	afterlife	240