Relation between start-ups' online social media presence and fundraising

YANG, Song and BERGER, Ron <http://orcid.org/0000-0002-6356-5506>

Published version

YANG, Song and BERGER, Ron (2017). Relation between start-ups' online social media presence and fundraising. Journal of science and technology policy management, 8 (2), 161-180.

Relation Between Start-ups' Online Social Media Presence and Fundraising

Abstract

The emergence of social media such as Facebook and Twitter have changed the way human beings communicate and interact in the context of business settings. In order to further explore the use of social media for entrepreneurs, we have explored how entrepreneurs use social media for fund-raising purposes. The novelty of this study is the use of social relationships (represented by social network features) as the main way to predict whether or not funding investments will occur. We use Application Programming Interfaces (APIs) to collect entrepreneurs' funding data from Crunchbase and entrepreneurs' social media data from Facebook and Twitter. We selected 123 companies in the "web" and "software" industries from Crunchbase. All the companies use Facebook and Twitter for fundraising purpose. Our results show that social media is significant for start-ups in their success or failure in fund raising. Investing energy into utilizing online social media and exhausting these platforms consciously contributes to the financial success of start-ups. Therefore, start-ups which are popular among online fans and followers can manage to raise larger amounts of funding in the early stages if it's done correctly.

Introduction

Network-based research in entrepreneurship continues to develop and grow for more than a decade. Among all the studies, core relational and structural constructs of social networks are the main focus in the field of entrepreneurship (Elfring & Hulsink, 2003; Hite & Hesterly, 2001; Hoang & Antoncic, 2003; Hoang & Yi, 2015). As social media has renovated the communication and interaction between individuals throughout the world, social media is also utilized as an essential tool by entrepreneurs to maintain relationships (Kadam & Ayarekar, 2014). According to Wasserman and Faust (1994), in a social network, relational ties between actors are channels for the transfer or “flow” of resources. In other words, actors and ties are the two components of a social network. Previous studies also indicate that online social networks are connected to offline social networks (Subrahmanyam et al., 2008). While the topic of funding investments is one of the most widely discussed topics in the realm of investing and business, few studies provide evidence as to how start-ups can increase funding investments from investors (Liang & Yuan, 2016). One way to understand how start-ups can increase their chances of receiving funding investment from investors is to understand one's business networking behavior.

Previous studies show that the emergence of online networking has opened the door for innovative companies to connect with each other and to operate more efficiently (Ellison, 2007; Ross et al., 2009). Although it is apparent that not all entrepreneurial undertakings contribute similarly to economic development, knowledge-based enterprises lead to the revitalization of the economy by prompting innovation, competition and industry dynamics (Brüderl & Preisendörfer, 1998; Burt, 1992). However, many early-stage businesses still face a lack of capital and background information about markets and competition that interfere with their future opportunities. Researching entrepreneurial success and failure in relation to one's online social presence may improve the survival and growth of their start-up business. Venture capital investment plays a crucial part in entrepreneurial practices. Funding plays an indispensable role in the evolution and eventual success of new ventures. Fundamentally, a strong social network with funding sources, opportunities for the start-up, by granting them access to superior information about new ventures and the environmental conditions they face (Alexy et al., 2012).

The popularity of online social networking sites provides a new platform for socialization and business activities (Ellison, 2007; Ellison et al., 2014; Kaplan & Haenlein, 2010). Social media, and in particular social network sites, are relatively recent additions to many individuals’ communication technology repertoires (Quinn, 2016). Social media acts as a powerful platform for communicating brand value and brand attributes by facilitating open forms of communication (Kadam & Ayarekar, 2014). Previous studies mainly focused on social media as a marketing tool for promoting products and attracting consumers, but recently a growing number of entrepreneurs have realized its potential in attracting funding (Clark & Melancon, 2013; Kadam & Ayarekar, 2014). According to Liang and Yuan (2016), entrepreneurs with broader social networks are more likely to receive funding from investors and accomplish business development. On the other hand, Tan and Tan (2012) explored the roles played by online and offline communities and discovered that offline communities have greater influence on investing behaviors.

Social media provides entrepreneurs with new information and resources to support their businesses (Choi and Berger, 2010). Online social networking sites disregard geographic boundaries, thereby providing one with free flow of information and worldwide connections, which in turn accelerates opportunity recognition and implementation (Choi and Berger, 2011). Taking into consideration the relevance of network building and the increasing number of social media users, the question arises: how can innovative, fast-growing businesses benefit from inherently free social media platforms to run their businesses more efficiently and raise funds?

Research has highlighted that financial capital is one of the fundamental challenges for start-ups (Cassar, 2004; Zhang, 2015). As a result, establishing better and wider professional relationships could support start-ups in reaching potential supporters and investors. Previous studies have shown shows that actively managing, grooming and maintaining one's online social network contributes to social capital (Ellison et al., 2014). Hong (2013) discussed that an increasing number of venture capitalists rely on social media to monitor promising start-ups' social-media efforts to assess their investment potential. Other studies also provided evidence as to how entrepreneurs can increase funding investments from investors by using social media (Alexy et al., 2012; Liang & Yuan, 2016).

The opportunities of fast-growing social media platforms such as Facebook, Twitter, Instagram and LinkedIn should be researched more in-depth since they have changed the way entrepreneurs communicate and interact with a variety of stakeholders. These platforms offer entrepreneurs new opportunities for accessing information and resources (Song, 2015). Therefore, this research focuses on the added value created by social media and examines their impact on entrepreneurs' fundraising efforts. Using quantitative research methods, this study analyses the importance of online social networks for the successful launch of start-ups. In particular, we aim at studying the relationship between start-ups social media activities and the amount of funding they raise.

Theoretical Framework

Start-ups are technology-based, new companies that are beyond the phase of idea or concept and have already established their legal infrastructure (Autio, 1997). Start-ups are considered as fledgling, knowledge-intensive business firms that have promising ideas and exhibit the ability to grow rapidly in a relatively short time (Hechavarr et al., 2016). Start-ups are able to convey a new product or service under circumstances of extreme uncertainty (Ries, 2011). Start-up success is embedded in a broad set of skills and expertise of the entrepreneur such as human and financial capital and access to networks (Gompes & Leruer, 2001). However, start-ups usually cannot build on the entrepreneur's human and financial capital alone (Tatarko & Schmidt, 2016). Therefore, online and offline networks are crucial for them to get the necessary financial and knowledge resources needed to succeed (Wu, 2007).

Research has indicated that start-up founders usually find it difficult to raise funds (Davila et al., 2003). Most of them are not eligible for bank loans or debt due to the fact that their businesses' operating history is limited. Some entrepreneurs are able to get funding from "family, friends and fools" (from the so-called three Fs) but in many cases it is not sufficient (Mason, 2007). In the context of offline networks, Baron and Markman (2003) found a positive relation between social business networks and financial success. Effective network building is considerably more important for early-stage companies (Burt, 1992; Hoang & Antoncic, 2003; Hoang & Yi, 2015) since networks offer the access to information, goods and services, expressions of affects, support and advice (Tichy et al., 1979). In the era of the Internet, social media has become a prevalent and key source of information sharing (Choi & Berger, 2011). It eliminates the barriers of time and space, and broadens the way entrepreneurs communicate, build networks, and how they obtain financial support. Online interactions have now filled the communication gaps of offline communication (Wellman et al., 2001) and hence become more important to understand.

From the concept of network content, social media allows entrepreneurs to gain the access to a variety of resources (Hoang & Yi, 2015). Hampton and Wellman (2003) examined the online networks of various local communities and found a positive effect of one's social interaction with social capital attainment. This can be seen as a result that online social networks let firms engage in discussions, share information and connect with others such as customers, employees, communities, analysts and investors. It is has been illustrated that companies' sales and marketing results have improved due to their social media presence (Clark & Melancon, 2013; Fischer & Reuber, 2011; Mangold & Faulds, 2009). Furthermore, online networking and specific structural properties of these networks can contribute to firms' success (Nann et al., 2010). However, whether the growth in online network size and network fan/follower activity helps achieve milestone events such as fund raising is a question worthwhile to study. We assume that online social networking sites lead to supportive opportunities in business development and accelerate young firms' recognition and expansion on the market. In this paper, we will examine start-up activities on Twitter and Facebook in order to expand their professional network and raise funds. We intend to shed light on the connection between start-ups' online activities and the amount of financial support received from investors. Our main hypothesis is that funders have a tendency to invest in start-ups with which they share certain social relationships, in terms of whether the funder and the start-up in question are similar or dissimilar. That is, this study combines social network analysis with the study of investing behavior.

Conceptual Framework

Network size

Network size refers to the number of network actors (Burt, 1983). Network size is one of the important structural characteristics in the context of entrepreneurship research (Hoang & Yi, 2015; Semrau & Werner, 2014). The larger the network is, the greater the amount of information circulates in it (Clark & Melancon, 2013). Previous research illustrated that the size of the network has a positive influence on entrepreneurial success (Baum et al., 2000; Hansen, 1995) and that the size of social networks is positively associated with the success of early-stage start-ups (Brüderl & Preisendörfer, 1998; Hoang & Antoncic, 2003; Hoang & Yi, 2015). According to Witt's model (2004) the more contacts an entrepreneur has, the more support he receives, which positively influences the success of start-ups, an engine that drives capital attainment. Larger networks are expected to pay off because network contacts provide access to resources, and the size of a network indicates how many different resource holders nascent entrepreneurs can potentially rely on when trying to establish their ventures (Berger and Gavish, 2015; Semrau & Werner, 2014). Furthermore, the number and strength of ties that a funder has with its peers and entrepreneurs is thus an indispensible source of information it may use to leverage its portfolio investments (Alexy et al., 2012). Thus, the more connections a start-up has, the higher the likelihood that funders will become aware of new high-quality investment prospect.

From online social network perspective, there are several studies in the field showing a positive effect of larger or more diverse networks (e.g., Raz & Gloor, 2007; Stam & Elfring, 2008) on stronger network relationships (e.g., Lee & Tsang, 2001). Lechner et al. (2006) claimed that there is a positive relationship between network size and performance. In this paper the number of fans and followers serves as a proxy for network size. We notice the size of online networks exceeds dramatically that of offline connections. Based on previous studies, a positive relation is expected between the online network size of a start-up and the total amount of funding rose. The following hypotheses are formulated.

Hypothesis 1: The size of a start-up's online network is positively related to the total amount of its funding raised.

Social media activity of users: Fan activity score and Follower activity score

Besides monitoring a company's online community size, the fraction of its active fans or followers, who frequently share, like or comment online content, also identifies whether social media presence is beneficial. Previous studies such as Clark & Melancon (2013) and Kadam & Ayarekar (2014) show that social media activities are relevant as a marketing tool or building relationships. Social media users share a vast amount of content on social media platforms every day. According to Gundecha and Liu (2012), "Social media data are largely user-generated content on social media sites. Social media data are vast, noisy, distributed, unstructured, and dynamic". The large amount of data that social media contains can help us understand human behaviors in difference fields (Clark & Melancon, 2013; Gilbert & Karahalios, 2009; Midkiff et al., 2015). In addition, they might contain valuable and beneficial data for businesses, users and consumers (Gundecha & Liu, 2012).

Social media platforms provide supplemental tools for page admins to calculate a useful metric, the so-called "Engagement Rate". It interprets the proportion of a page's audience engaged with its content. On Facebook it is available under the "Page Insights" function. Facebook Engagement Rate takes into account the total number of likes, comments and shares. Then the total can be multiplied by the number of fans to provide a percentage measurement (Socialbakers, 2015). Similarly, we can also calculate Twitter Engagement Rate by using the same method. Number of replies, retweets and mentions of the tweets are added up. To get a percentage rate, the total is multiplied by the number of followers (Socialbakers, 2015). However, some of these metrics are post metrics, while some are not available to the public. Therefore we designed our own measurement scale to calculate engagement. The value of relationships is measured by "Facebook fan activity score" and "Twitter follower activity score", which are estimated on the basis of the retrieved metrics. We assume companies that build an active online community show better business performance and can increase their awareness more easily. In this study performance is indicated by the amount of total funding, engagement rate is indicated by activity score. Based on the above discussion the following hypothesis is created:

Hypothesis 2: The more active fans/followers a company has on Facebook/Twitter, the more funding it raises in total.

Frequency of social media usage

Burt (1992) found that the amounts of time and effort invested in building social capital further contribute to business success. In the area of social sciences, researchers found that the time spent on social media is relevant to frequency of communication (Cirillo et al., 2015; Fischer & Reuber,2011). Assuming that crowd funding founders use social media as a tool to attract funding, the time they spend on maintaining existing and building new relationships online should be important when considering their success in raising capital. In our research, it is represented by the number of their posts and tweets. Positive relationships among the intensity of entrepreneurs' social interactions through Twitter and Facebook is slated to have a positive effect on capital attainment. Therefore, we hypothesis that:

Hypothesis 3*：*The number of posts and tweets is positively related to a start-up's total amount of funding.

Venture capital

Venture capital is defined as equity or equity-based investment in recently established companies by financial intermediaries, which invest in early-stage businesses. Venture capitalists are considered as investors who provide start-ups with more than just financial help. In return for the high risk of investment, besides ownership, venture capitalists get control over the company. They often play the role of director, advisor or manager of the firms due to their rich knowledge of markets and professional experience (Kortum & Lerner, 2000). Venture-backed companies are proved to be more innovative and more successful due to venture capitalists' additional (i.e., non-financial) support (Hellmann & Puri, 2002; Kortum & Lerner, 2000). Venture capital funding events are considered as a positive sign of the quality of start-ups (Davila et al., 2003). Baron and Markman's research (2003) suggested that companies with broader social networks receive venture funding more easily. Based on the above discussion, the following hypothesis is formulated.

Hypothesis 4: The broader and more active an entrepreneur's network on Twitter (number and activity score of followers) and Facebook (number and activity score of fans), the more likely it will rise venture capitalist funding.

Stages of start-up funding

Start-ups face the challenge of gaining awareness and trust of people, especially investors', to get access to necessary resources (Liang & Yuan, 2016). Wu (2007) argued that network building increases the chance to gain funding in general (Stam & Elfring, 2008). Thus, in order to increase awareness and gain credibility through online platforms, the quality of the content and the activity of the companies are crucial. In this case, these can be measured by the number of users and by the number of posts. As discussed previously, the type of information might change in line with the start-ups venture phase (Elfring & Hulsink, 2003; Hoang & Antoncic, 2003). In addition, Greve and Salaff (2003) explored that each phase of establishing a business requires different types of network activities. Entrepreneurs tend to limit their activities in the initial phase of their progress, as they may not feel confident about their business plan and abilities (Tan & Tan, 2012). However, after the start-up is incorporated and their business is set up, one seems to be more inclined to share more about their ideas and needs with their network and hence, get support, attract potential business partners, and funding. The following hypothesis is formulated:

Hypothesis 5: After a business is established, start-ups become more active on social media sites to attract their network's attention. Social media activity increases between the first few rounds of funding. Based on our hypotheses, we generate our conceptual model (Figure 1).

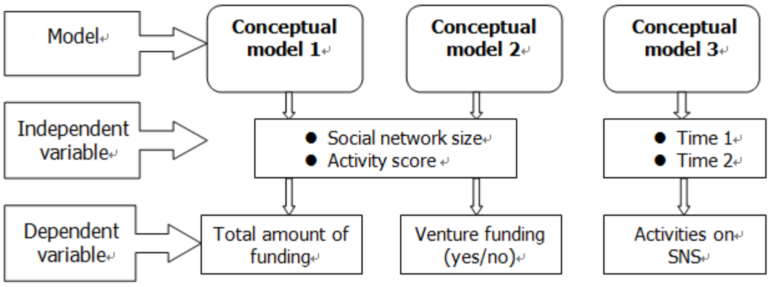

Figure 1 Conceptual model

Research design and data collection

This research relies on a wide range of quantitative data, which was obtained from three different online sources which includes Facebook, Twitter and CrunchBase. Facebook and Twitter are the two social media platforms that the entrepreneurs use for fundraising (Priem & Hemminger, 2010). Crunch Base is a database of the start-up ecosystem consisting of investors, incubators and start-ups. It is constantly reviewed by editors to ensure that its data is up-to-date and reliable. The CrunchBase dataset is a formidable dataset to employ for social analysis as it covers almost complete relationships between start-ups and venture capitalists (Alexy et.al, 2012). The dataset of Crunch Base has been used in prior studies as well, however, all of these researches examined other fields of investor and start-up behaviour and activity (Eugene & Yuan, 2012; Xiang et al., 2012). CrunchBase can be best viewed as a ‘‘repository’’ of start-up companies, individuals, and investors having a focus on U.S. high-tech sectors (in particular IT and Internet). CrunchBase describes itself as a ‘‘free database of technology companies, people, and investors that anyone can edit.’’ As the database includes privately held firms with very few employees as well as multi-billion dollar businesses, the spectrum of firms included is wider compared to other company databases. The data was retrieved by using Application Programming Interfaces (APIs), which enables the collection of novel metrics, from various sources that provide a well-structured dataset. The CrunchBase dataset is a formidable dataset to employ for social network analysis as it covers almost complete relationships between start-ups and funders. The relationships between start-ups and VCs are materializing through investments (i.e., funding rounds). This is thus the point of departure for calculating the network metrics on the start-up network. Using the data set from CrunchBase, we build a CrunchBase social network based on the entity and relationship types, where nodes represent entities, while relationships represent edges.

Data sample

Information about start-up companies as well as data about their funding was collected from the CrunchBase website. CrunchBase is a database of the start-up ecosystem consisting of investors, incubators and start-ups. It is constantly reviewed by editors to ensure that its data is up-to-date and reliable (Alexy et al., 2012). The dataset of CrunchBase has been used in prior studies as well, however, all of these researches examined other fields of investor and start-up behaviour and activity (Eugene & Yuan, 2012; Xiang et al., 2012).The database covers privately held companies with very few employees as well as multi-billion dollar businesses, the spectrum of companies included is wider compared to other company database (Alexy et al., 2012). For this research data was extracted by using the CrunchBase

Application Programming Interface (API). Using CrunchBase API provides access to its free directory of technology start-up companies.

First of all, our database included 37,875 companies with recorded fundraising until April 2014. Companies were categorized by industry; country; status; date of founding; date, round and amount of raised funding. Our research was conducted on start-up companies, operating in the U.S, which has been the leader in churning out start-ups globally (Tan & Tan, 2012). As the purpose of our research is to check how start-ups using social media to collect funding, thus is a strong foundation for research. We selected firms from two high technology sectors: “web” and “software” (company category names are used by CrunchBase). The selection criteria were also supported by CrunchBase’s report, which was carried out by its data export tool as shown in Figure 2. Web and software companies were among the top company categories in terms of total amount of received funding between 2000 and 2014. Furthermore, according to the Facts and Figures of the Inc. 5000 report1, companies that are operating in the Software and IT services industry performed 136% and 111% aggregated growth in terms of revenues respectively.

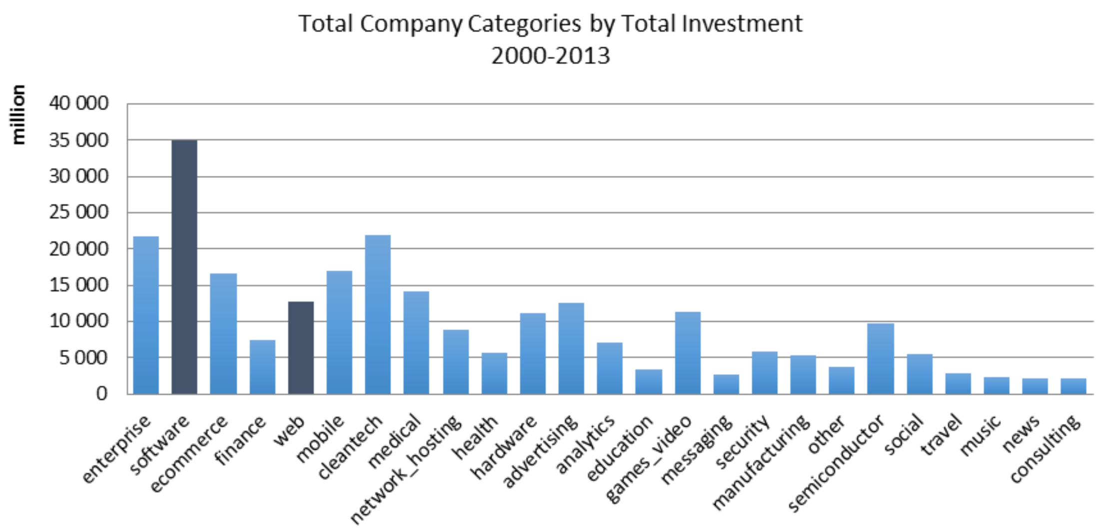

Figure 2: Top company categories by amount of funding 2000-2013

Source: www.crunchbase.com

Second, we dropped the start-ups that are no longer running. Since the study uses social media data, companies without active social media account on Facebook and Twitter were also removed from our sample. Due to the fact that social media traffic increased steadily after 2009 (Quinn, 2016). We selected companies that found after 2009 in order to obtain enough social media data. Based on all the criteria we’ve mentioned above, a sample of 123 companies was selected for analysis.

Dependent variables

The amount of funding raised represents the dependent variable in this study. The amount of funding was calculated both as a sum score as well as separate scores distinguished by type of funding.

Independent variables: Social media metrics

Social media activity of the selected start-ups was monitored between 2009 and 2014. Social media metrics of each selected start-up company were extracted from Facebook and Twitter, for instance the number of fans or followers, and the amount of content (posts, tweets, images, shares or other content). The metric of presence, interactivity and reach are necessary to determine the traffic of a social media page. Sterne (2010) argued that the size of a company's online social network does not have an important role in its success in social media. What matters most is how many people find its online content remarkable and then spread the word through sharing or retweets.

Facebook

Facebook metrics were collected through the use of Facebook Graph API. The following variables were studied:

- Fans: refers to the number of Facebook users who "like" the company's Facebook page.
- Posts: refers to the number of how many times a day a company posted content to its page.
- Likes: reveals how many "likes" a company's post got each day.
- Comments: shows how many times a day users commented on a firm's Facebook posts
- Shares: reveals how many times a company's Facebook content was shared by users each day.
- Fan activity score: measures what fraction of a Facebook pages (in this case a start up's) contents (posts) have caught its fans' attention. For this report the metric of "fan activity score" is calculated based on the retrieved metrics (introduced above). First daily fan activity score was calculated for each start-up for 5 years as follows:
- Then the average of the daily activity scores was estimated for each company.

Twitter

Likewise data mining on Facebook, Twitters' API - so called REST API v1.1 - was applied for data collection. However, in contrast with Facebook's database, access to Twitter data is limited, only a limited number of calls can be made in a certain time period. This study analysed the following variables:

- Followers: number of users who have chosen to follow the company.
- Tweets: reveals how many times a company sent new content to its Twitter page.
- Retweets: reflects the number of times that a company's tweet was retweeted by its followers.
- Favorites: similar to Likes on Facebook, it represents the volume of engagement of Twitter users.
- Follower activity score: Twitter activity score on Twitter also indicates how a company or brand engages its followers on Twitter. Calculation was done similarly, as done for Facebook fans. First the daily Twitter activity score for all start-ups was calculated with the following formula between 2009 and 2013: Then the average amount of the daily activity score was estimated for each company.

Data reduction and analysis

The data file was created in Excel and subsequently converted into a format that is recognizable in SPSS, where variables were defined in SPSS. Since the dataset did not contain any counter-indicative items, recoding was not necessary. Scales were not used, therefore tests of reliability and validity was not part of this analysis. After defining the codebook, the data was first reviewed for missing data, of which none was detected; hence, the total sample of 123 was retained for further descriptive analysis. Descriptive analysis was conducted first, followed by regression analysis (Model 1 & 2) and ANOVA analysis (Model 3) for hypotheses testing.

Data Analysis

Model 1

Descriptive statistics

The frequencies table (see Table 1) shows that 123 companies were analysed, and as aforementioned no missing data was detected. The average value of the total amount of funding was $7,766,052.

Table 1: Frequencies table

Statistics								
		Totalfunding	Fans	Followers	Posts	Tweets	FbActSc	TwActSc
N	Valid	123	123	123	123	123	123	123
	Missing	0	0	0	0	0	0	0
Mean		7 766 052	42 078	18 765	651	1 402	5,41	1,51
Median		1 816 666	997	1 270	303	1 344	0,21	0,18
Mode		300000a	45a	132a	-	-	-	0,00
Std. Deviation		14 039 388	197 560	118 503	1 083	1 101	32,55	4,76
Skewness		3,00	6,45	10,47	4,24	0,22	9,42	4,73
Std. Error of Skewness		0,22	0,22	0,22	0,22	0,22	0,22	0,22
Kurtosis		9,65	43,25	113,38	24,36	- 1,44	94,75	22,77
Std. Error of Kurtosis		0,43	0,43	0,43	0,43	0,43	0,43	0,43
Minimum		25 000	8	10	-	-	0,00	0,00
Maximum		78 000 000	1 537 254	1 296 668	8 479	3 220	340,48	29,21
a. Multiple modes exist. The smallest value is shown								

Correlation analysis was used to quantify the strength and direction of the linear relationship between each pair of variables. Due to the fact that this study aims at using parametric statistics (e.g. Pearson correlation) all variables had to satisfy several assumptions. Outliers were detected because they could have altered the results of the analysis. Extreme outliers were removed to identify a more accurate model that accommodates unusual cases. Consequently 119 cases remained in the analysis. To use a Pearson's correlation test, the assumption of bivariate normality must be satisfied. The normality of the variables' distribution was tested by using the Kolmogorov-Smirnov statistic, which assesses the normality of the distribution of scores. A non-significant result (Sig value should be more than .05) indicates normality. In this case the Sig. value was 0 for each group of variables, suggesting violation of the assumption of normality.

To be a valid test of strength, all variables were transformed in a way that corresponds to the size of the deviation from the normal distribution. The type of transformations depends on the shape of the scores' distribution. Therefore, the skewness and kurtosis values of the variables were checked. Based on the output table, values showed positively skewed and peaked distribution, which also refer to non-normal distribution. Logarithm and square root transformations were applied. After the transformations normality tests were carried out again, however, the scales did not follow normal distribution for all variables. Although the assumption of normality is violated, Pearson's correlation model was chosen on the basis of the following studies. On one hand, according to Rasmussen and Dunlap's (1991) observation study on non-normally distributed variables, parametric analyses of transformed data proved to be more powerful than nonparametric analysis of untransformed data. Furthermore, the Pearson correlation is considered to be robust and it withstands violations of normality (Bishara & Hittner, 2012). The critical values for correlation coefficients were calculated at the .05 level of significance based on the sample size (See Table 2 and Table 3).

Table 2: Correlation coefficients

Critical values for r	
N	119
p < .10	0,15
p < .05	0,18
p < .01	0,24
p < .001	0,30

Table 3: Strength of correlation

Critical values for r	Strength of Association
0.1 < | r | < .3	small correlation
0.3 < | r | < .5	medium/moderate correlation
| r | > .5	large/strong correlation

The correlation table shows how the variables are correlated and moving together. Results of the Pearson correlation analysis are presented in table 4 and table 5.

Table 4: Correlation Table – Twitter

	Total Funding	Followers	Tweets
Followers	,31*		
Tweets	,17	,49*	
FollActSc	,05	,29*	,33*

Note: *=statistically significant at p<.05 level.

Table 5: Correlation table – Facebook

	Total Funding	Fans	Posts
Fans	,29*		
Posts	,07	,58*	
FanActSc	,35*	,61*	,52*

Note: *=statistically significant at p<.05 level

Twitter

As shown in Table 4, there was positive and significant correlation between the following variables:

- Total amount of a company's received funding and the number of its followers on Twitter, r=.31, p<0.0005
- Number of followers and number of tweets, r=.49, p<0.0005

- Number of tweets and Follower activity score (FollActSc), $r=.33$, $p<0.005$
- Number of Twitter followers and Follower activity score, $r=0.29$, $p<0.0005$

Overall, there was a positive correlation between a start-ups' number of Twitter followers and the total amount of its funding. Furthermore positive, inter-correlation was found between social media metrics namely; between the number of followers and the number of tweets, and between the number of tweets and the value of follower activity score. There was positive, small association between the number of followers and the follower activity score.

Facebook

Positive, significant relationship was observed between the variables as follows:

- Total amount of funding and Fan activity score (FanActSc), $r=.35$, $p<0.0005$
- Number of Facebook fans and number of posted contents, $r=.58$, $p<.0005$
- Number of Facebook fans and value of Fan activity score (FanActSc), $r=.61$, $p<0.0005$
- Number of posts and Fan activity score (FanActSc), $r=.52$, $p<0.0005$
- Total amount of raised funding and the number of Facebook fans, $r=.29$, $p<0.0005$

To sum up, the results showed a positive, relationship between start-ups' total amount of funding and their fan activity score. A positive, small association was revealed between the total amount of raised funding and the number of Facebook fans. Furthermore, positive inter-correlation existed between the following independent variables: Facebook network size and number of posts, network size on Facebook and fan activity score, number of posts and fan activity score. Although VIF and tolerance values did not indicate the possibility of multicollinearity, results should be interpreted carefully due to the violation of the assumption of normality. In the next step we continued our regression analysis to test our hypotheses.

Multiple linear regression

To test the stated hypotheses, a multiple regression model was used. Multiple linear regression analysis was conducted to determine the relative contribution of each of the predictors to the total variance explained above. The conceptual model was tested for each social network, Twitter and Facebook, separately. To ensure the validation of the tests, several assumptions were held. Since many of them were checked by inspection of the residuals the regression analysis needed to be run. Initially, the analyses were run on "pure" variables to check the assumptions (Field, 2009). Results showed that assumptions were violated, therefore corrections needed to be done. First, outliers were deleted. Then the logarithm of dependent and independent variables were used instead of "pure" variables. Using logarithm transformation helps to minimize the relative standard deviation instead of the absolute one and lets the error term be closer to normality, additionally the influence of the possible outliers will be less severe. After the aforementioned corrections, assumptions were investigated again: linearity, multicollinearity and homoscedasticity were checked (Field, 2009). Coefficients and correlation tables were checked for multicollinearity. Correlations between the independent variables were not too high; VIF and tolerance values did not indicate the possibility of multicollinearity. All the assumptions passed the test allowing further analysis.

Model 1 for Twitter

The regression analysis showed whether the number of Twitter followers, the number of a company's tweets and its follower activity score have an effect on their raised amount of funding. The model reached statistical significance. As shown in table 6, the model explains 12.7% of the variance in total amount of funding (adjusted R^2). By analysing the results of the regression analysis, it could be observed that only the number of followers made a significant contribution to the total amount of funding (β=.337, p=.008). From these findings, the hypothesis 1 is accepted, hypothesis 2 and 3 are rejected.

Table 6: Regression coefficients table – Twitter

Predicting 'Total amount of funding'	**Beta**	**p**
Twitter followers	.337	**.008**
Follower Activity Score	.084	.933
Tweets	.023	.851

R^2=12.7%

Model 1 for Facebook

According to our ANOVA analysis, the model for Facebook was found to be statistically significant as a whole. It explains 21.3 % of the variance in total amount of funding (adjusted R^2) according to table 7. Two out of the three independent variables had significant influence on the total amount of received funding. Fan activity score made the largest unique contribution to the total amount of funding (ß=0.436, p=.001). Furthermore, the amount of the start-ups posted content on Facebook also made a statistically significant negative contribution (ß= -0.245, p=.017). Results showed that the number of Facebook fans (network size) on Facebook had no significant effect on the total amount of funding (ß=0.14, p=.269). From these findings, only hypotheses 2 is accepted and the hypothesis 1 and 3 are rejected. To sum up, the activity score of the fans showed an effect on the total amount of a start-up's raised funding. The network size did not have a significant influence on fundraising. However, it is quite surprising, that the amount of Facebook posts resulted with a negative ß, which can be explained by the importance and credibility of content.

Table 7: Regression coefficients table – Facebook

Predicting 'Total amount of funding'	**Beta**	**p**
Facebook fans	.140	.269
Fan Activity Score	.436	**.001**
Posts	-.245	**.017**

R^2=21.3%

Model 2- Logistic regression

Logistic regression was performed to ascertain the effects of network size and activity of fans and followers on Facebook and Twitter on the likelihood that start-up companies received venture funding. Assumptions of the test were checked. The logistic regression model was not statistically significant and indicated a poor fit. The model was tested again to correct the fit of the model. Predictors were included in the model separated for each social media site. However, the model did not prove to be significant. Consequently, hypothesis 4 is rejected.

Model 3- One-way repeated measures ANOVA

Due to the limitation of the applied program to retrieve social media data, this analysis was conducted only on Facebook activity metrics. This is because of the data limitation that can be accessed in a certain time period for Twitter. One-way repeated measures analysis of variance (ANOVA) was conducted to determine whether there were statistically significant differences in start-ups' Facebook activity at Time 1 (before 1st round of funding), Time 2 (1st round – 2nd round) and Time 3 (2nd round – 3rd round). Their activity was measured by the number of posts. Consequently only 123 start-ups were selected, which received funding at least three times. Assumptions of the analysis were tested in advance. The repeated measures ANOVA is fairly robust to violations of normality with large enough sample sizes (e.g. 30+) (Pallant, 2005) were examined. The means and standard deviations of the original date are presented in table 8 below.

Facebook activity of start-ups were statistically different at the various stages points during fundraising [Wilks' Lambda=0.822, $F(2, 38) = 4.121$, $p < .05$, multivariate partial eta squared = 0.178]. Table 8 and 9 show that start-ups became more active, the number of their posts increased at each successive time point (i.e. increasing at each stage). Contrast analysis showed obvious trends in the data sample. Consequently Hypothesis 5 is accepted.

Table 8: Descriptive Statistics

Descriptive Statistics			
Time period	**Mean**	**Std. Deviation**	**N**
Time1	34,2	104,6	40
Time2	118,7	366,7	40
Time3	232,1	518,4	40

Table 9: ANOVA

Multivariate Tests[a]							
Effect		**Value**	**F**	**Hypothesis df**	**Error df**	**Sig.**	**Partial Eta Squared**
time	Pillai's Trace	,178	4,121[b]	2,000	38,000	,024	,178
	Wilks' Lambda	,822	4,121[b]	2,000	38,000	,024	,178
	Hotelling's Trace	,217	4,121[b]	2,000	38,000	,024	,178
	Roy's Largest Root	,217	4,121[b]	2,000	38,000	,024	,178
a. Design: Intercept Within Subjects Design: time							
b. Exact statistic							

The findings suggest that the examined social media activities on both social media platforms—i.e., Facebook and Twitter—contribute differently to a start-up's total amount of received funding. Regarding Twitter, only one of the hypothesis proved to be statistically significant, which revealed that a company's online social network size has a significant impact on its total amount of funding. Hence, only hypothesis 1 was accepted. Concerning the assumptions about Facebook metrics, two of the independent variables made a significant unique contribution to the prediction of the total amount of funding raised. On one hand, the number of posts, which identifies the frequency of a start-up's social media usage, revealed a negative effect on fundraising. On the other hand, the average Facebook fan activity score of a start-up also showed significance. Hypothesis 2 was rejected and 3 was accepted. The explanatory power of the developed regression models (adjusted R-squared values) were relatively low. However, this does not represent a threat to the model's validity. In general, low R2values are common in behavioral science research (Chau & Hu, 2002). Hypothesis 4 was formulated on theories of venture investors, however, in this case assumptions were not met. Network size and activity score did not show any effect on venture funding, hypothesis 4 was rejected. Last but not least, social media activity was analysed between phases of fundraising. Analysing contrasts at different time points showed that the differences in start-ups' Facebook activity were significant. As start-ups started operating and obtained investment by funding rounds, their social media activity started to increase simultaneously and raised public awareness of businesses. Hypothesis 5 was supported.

Conclusion

Social capital in its various forms and contexts have emerged as one of the most salient concepts in social science. This is specifically due to the assumption behind social capital, that people invest in social relations and expect something in return (Soetanto and van-Geenhuizen, 2015). From a practical perspective, understanding network dynamics helps answer the question of which ties matter and when, especially in capital attainment. New firms that are inhibited by liability of newness ought to use their social networks to develop early reputation networks to foster firm development (Matthews & Reynolds, 2016).

Even though we recognize the contributions made by prior research, we find that there is a dearth of research systematically addressing how the characteristics of entrepreneurs' networks affect their access to needed resources (Alexy et al., 2012). Over the last few years numerous changes have occurred in the way people and firms share information and interact with each other. Social media has a pioneering role in the field of communication and connection with audiences. Social media increases the ability to create and maintain weaker ties, allowing a relatively larger number of connections to be maintained at once (Donath, 2007). Although online social networking developed as a consumer-driven service, entrepreneurs have now begun to exploit official and unofficial networks for capital attainment (Frydych et al., 2014). Social networks takes outdated ‘offline’ business processes into an online atmosphere, enabling entrepreneurs to cultivate and facilitate business development. Features such as online-based communities and interaction mechanisms produce novel settings for capital attainment, illustrating the potential for unique entrepreneurial procedures and potentially different success drivers. A more detailed study on the ways in which engagement with these media relate to social capital outcomes is warranted to better understand the dynamic of social media.

The aim of this research was to analyse an alternative way of getting financial support for start-ups, operating in the IT industry. We gathered data related to IT companies and their social media data. Quantitative analysis was conducted in order to test how start-ups use social media sites and how it in turn affects their fundraising abilities and success. Our analysis provided some interesting results and they support earlier qualitative studies (Alexy et al., 2012; Xiang et al., 2012; Liang & Yuan, 2016). We also strongly believe that the insights generated bear clear practical implications. Our results underline the often-cited claim that networking activities may be valuable for (nascent) entrepreneurs, as investing time and energy in extending a network and increasing relationship quality may facilitate access to needed resources. Funding investment behavior is a highly complex problem and we understand that there are more factors than those which are discussed and implemented in this study. More importantly, the problem is a non-linear one. Intuitively, we know that investors do not make funding investment decisions based on a single factor but rather on a plethora of factors. We claim that social variables are reasonable features for predicting funding investment behavior. Our results show that it is possible to predict funding investment behavior based on social relationships. Start-ups should take their social relationships into consideration when seeking investments from a prospective investor

Our research shows whether social media performance of start-ups have any effect on their raised amount of funding. Traditional media metrics were selected (Kaplan and Haenlein, 2010; Kietzmann et al., 2011) and implemented on Facebook and Twitter to analyse the performance of the selected start-ups: size, quality, and the intensity of social network. It is important to note that the analysis revealed different results between the different social media platforms. Even though, the same hypotheses were formulated and similar type of metrics were used for testing hypotheses on both social networking sites, some metrics showed different results on Facebook and Twitter. These results are in line with previous studies, which discussed the differences of social media sites and made some attempts to separate social media categories (Kaplan & Haenlein, 2010). Therefore start-ups might need to develop different strategies for different social media sites to make the most of them.

Although literature suggested that businesses with broader offline network show better performance (Brüderl & Preisendörfer, 1998; Hoang & Antoncic, 2003; Hoang & Yi, 2015), in this study the size of Facebook network did not show any influence on the amount start-ups’ funding. However, results indicated that start-ups, whose users are more active managed to raise larger amount of funding in total. What matters more is, if a company’s Facebook visitors find its content interesting and show their enthusiasm by engaging in conversations, liking and sharing posts. Therefore it is important to share valuable content that grabs attention and makes people want to share and start a discussion. The more shares, likes and comments a post receives, the more likely it reaches broader audience and arouses supporters' attention. The findings of this research suggested that too many Facebook posts can influence start-ups' fundraising process negatively. Again, it can be explained by the importance of the content quality. As discussed above, the content of posts matters more than the quantity.

It is important to note that Twitter analysis had some limitations therefore, conclusions should be interpreted carefully. Due to the data regulation, only a limited amount of data could be collected by Twitter API. In the case of Twitter analysis, one out of three hypotheses was supported. Only network size showed a correlation with the total amount of funding. In contrast with Facebook, this outcome supports studies about benefits of network size and social capital. Hong (2013) also found that some investors were impressed by start-ups' growing number of Twitter followers. In this research other metrics did not make significant contribution to the total amount of funding received. Hence, it is for start-ups with effective social media strategy are more likely to raise larger amount of funding in total.

Results of logistic regression did not support the theory that the broader the social network is, the better the chances are to raise venture capital (Baron & Markman, 2003).Therefore it cannot be concluded that social media has a specific effect on the type of funding. One-way repeated measures ANOVA was used to compare Facebook activity of start-ups between their rounds of funding. Results indicated that as start-ups started operating and became more successful, they also started putting more effort into using online social media. It shows that social media does count for businesses, even for small, early-stage start-ups (Ellison et al., 2007; Ross, 2012). Survival, performance, and progress of the entrepreneurial firm are at the core of entrepreneurship research (Lechner et al., 2006). Entrepreneurial firms are characterized by a lack of internal capital and articulated in the theoretical research with the liability of newness and of smallness. Networking has been found to be important for entrepreneurial firms.

Online social networking is increasing and this study showed that it is influencing start-ups' performance and has managed to indicate new findings in the field of online social networking. Although small results were found, they showed that innovative start-up companies were able to benefit from communicating on social media platforms. Start-ups, which were using Facebook and Twitter effectively, focusing on valuable social media metrics, received larger amount of funding in total. Furthermore, it was observed that as their business grew, they intended to put more effort into online social networking. It confirmed the idea that businesses are using social media consciously.

However, using social media to attract investors is still new and intriguing, however it is expected that they will have a valuable role in the future. Gunelius (2013) supported this idea, as she stated: "Using social media to communicate investor information is new today. It will become one of the primary investor relations communication tools in the future. "As it is still controversial in what extent social media will change the business world, it is recommended to conduct further researches.

References

Alexy, O. T., Block, J. H., Sandner, P., & Ter Wal, A. L. (2012). Social capital of venture capitalists and start-up funding. ***Small Business Economics***, 39(4), 835-851.

Autio, E. (1997). New, technology-based firms in innovation networks symplectic and generative impacts. ***Research policy***, 26(3), 263-281.

Avinash, R. and Soyjaudah, K.M.S. (2016). Information security governance for e-services in southern African developing countries e-Government projects, J***ournal of Science & Technology Policy Management***, 7(1), 26 - 42.

Baron, R. A., & Markman, G. D. (2003). Beyond social capital: The role of entrepreneurs' social competence in their financial success. ***Journal of Business Venturing***, 18(1), 41-60.

Baum, J. A., Calabrese, T., & Silverman, B. S. (2000). Don't go it alone: Alliance network composition and start-ups' performance in Canadian biotechnology. ***Strategic management journal***, 267-294.

Berger, R. & Gavish, Y. (2015). A Gem in a hostile world: An evolutionary analysis of the diamond industry: The case of the Israeli diamond industry, ***International Journal of Strategic Change Management***, 6(3/4), 268-291.

Bishara, A. J., & Hittner, J. B. (2012). Testing the significance of a correlation with nonnormal data: Comparison of pearson, spearman, transformation, and resampling approaches. ***Psychological methods***, 17(3), 399.

Brüderl, J., & Preisendörfer, P. (1998). Network support and the success of newly founded business. ***Small business economics***, 10(3), 213-225.

Burt, R. S. (1983). Corporate profits and cooptation: Networks of market constraints and directorate ties in the American economy. Academic Press.

Burt, R. S. (Ed). (1992). Structural holes:The social structure of competition Cambridge, MA: Harvard University Press.

Cassar, G. 2004. The financing of business start-ups. ***Journal of Business Venturing***, 19(2), 261-283.

Chau, P. Y., & Hu, P. J. H. (2002). Investigating healthcare professionals’ decisions to accept telemedicine technology: an empirical test of competing theories. ***Information & management***, 39(4), 297-311.

Choi, J. C. & Berger, R. (2010). Ethics of celebrities and their increasing influence in 21st century society, ***Journal of Business Ethics***, 91:313-318.

Choi, J. C. & Berger, R. (2011). Globalization, property rights and knowledge networks", ***International Journal of Technology Management***, 56(1), 53-72.

Cirillo, C., Diana, M., & Dong, H. (2015). Time spent on social media and its impact on travel behaviours and activity participation: Results from a comparative study based on association analysis and discrete choice models. In IATBR 2015-WINDSOR, July.

Clark, M., & Melancon, J. (2013). The influence of social media investment on relational outcomes: A relationship marketing perspective. ***International Journal of Marketing Studies***, 5(4), 132-142.

Davila, A., Foster, G., & Gupta, M. (2003). Venture capital financing and the growth of start-up firms. ***Journal of business venturing***, 18(6), 689-708.

Donath, J. (2007). Signals in social supernets. ***Journal of Computer‐Mediated Communication***, 13(1), 231-251.

Elfring, T., & Hulsink, W. (2003). Networks in entrepreneurship: The case of high-technology firms. ***Small business economics***, 21(4), 409-422.

Ellison, N. B. (2007). Social network sites: Definition, history, and scholarship. ***Journal of Computer-Mediated Communication***, 13(1), 210-230.
Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook "friends:" Social capital and college students' use of online social network sites. ***Journal of Computer Mediated Communication***, 12(4), 1143-1168.
Ellison, N. B., Vitak, J., Gray, R., & Lampe, C. (2014). Cultivating social resources on social network sites: Facebook relationship maintenance behaviors and their role in social capital processes. ***Journal of Computer-Mediated Communication***, 19(4), 855-870.
Eugene, L. Y., & Yuan, S. D. (2012). ***Where's the money? the social behavior of investors in facebook's small world***. Paper presented at Proceedings of the 2012 International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2012).
Field, A. (2009). ***Discovering statistics using SPSS*** Sage publications.
Fischer, E., & Reuber, A. R. (2011). Social interaction via new social media: (How) can interactions on twitter affect effectual thinking and behavior? ***Journal of Business Venturing***, 26(1), 1-18.
Frydrych, D., Bock, A. J., Kinder, T., & Koeck, B. (2014). Exploring entrepreneurial legitimacy in reward-based crowdfunding. ***Venture Capital***, 16(3), 247-269.
Gilbert, E., & Karahalios, K. (2009). ***Predicting tie strength with social media***. Paper presented at Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.
Greve, A., & Salaff, J. W. (2003). Social networks and entrepreneurship. ***Entrepreneurship theory and practice***, 28(1), 1-22.
Gompers, P. & Lerner, J. (2001). The venture capital revolution. ***Journal of Economic Perspectives***, 15(2), 145–168.
Gundecha, P., & Liu, H. (2012). Mining social media: A brief introduction. ***Tutorials in Operations Research***, 1(4).
Gunelius, S. U. S. A. N. (2013). Why you need to prioritize responsive design right now. Accessed June, 17, 2014.
Hampton, K., & Wellman, B. (2003). Neighboring in netville: How the internet supports community and social capital in a wired suburb. ***city and community***, 2(4): 277-311.
Hansen, J. H. (1996). Analysis and compensation of speech under stress and noise for environmental robustness in speech recognition. ***Speech communication***, 20(1-2), 151-173.
Hechavarr, D.M., Matthews, C.H., and Reynolds, D. P. (2016). Does start-up financing influence start-up speed? Evidence from the panel study of entrepreneurial dynamics", ***Small Business Economy,*** 46, 137–167.
Hellmann, T., & Puri, M. (2002). Venture capital and the professionalization of start-up firms: Empirical evidence. ***The Journal of Finance***, 57(1), 169-197.
Hite, J. M., & Hesterly, W. S. (2001). Research notes and commentaries. the evolution of firm networks: From emergence to early growth of the firm. ***Strategic Management Journal***, 22(3), 275-286.
Hoang, H., & Antoncic, B. (2003). Network-based research in entrepreneurship: A critical review. Journal of business venturing, 18(2), 165-187.
Hoang, H., & Yi, A. (2015). Network-based research in entrepreneurship: A decade in review. ***Foundations and Trends (R) in Entrepreneurship***, 11(1), 1-54.
Hong, N. (2013). If you look good on twitter,VCs may take notice. ***The Wall Street Journal***.

Kadam, A., & Ayarekar, S. (2014). Impact of social media on entrepreneurship and entrepreneurial performance: Special reference to small and medium scale enterprises. ***SIES Journal of Management***, 10(1).

Kanda S, Kulthida, T., and Wasu, C. (2015). Factors affecting the development of e-government using a citizen-centric approach, ***Journal of Science & Technology Policy Management***, 6(3), 206 - 222.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! the challenges and opportunities of social media. ***Business horizons***, 53(1), 59-68.

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. ***Business horizons,*** 54(3), 241-251.

Kortum, S., & Lerner, J. (2000). Assessing the contribution of venture capital to innovation. ***RAND journal of Economics***: 674-692.

Mangold, W. G., & Faulds, D. J. (2009). Social media: The new hybrid element of the promotion mix. ***Business horizons***, 52(4), 357-365.

Lechner, C., Dowling, M., & Welpe, I. (2006). Firm networks and firm development: The role of the relational mix. ***Journal of business venturing***, 21(4), 514-540.

Lee, D. Y., & Tsang, E. W. (2001). The effects of entrepreneurial personality, background and network activities on venture growth. ***Journal of management studies***, 38(4), 583-602.

Liang, Y. E., & Yuan, S. T. D. (2016). Predicting investor funding behavior using crunchbase social network features. ***Internet Research***, 26(1), 74-100.

Mokter, H., Zahidul, I., Abu Sayeed, M., and Kauranen, I. (2016). A comprehensive review of open innovation literature, ***Journal of Science & Technology Policy Management***, 7(1), 2-25.

Mason, C. (2007). International handbook series on entrepreneurship. In S. Parker (Ed.), ***The life cycle of entrepreneurial ventures***, 3, 259-299 Springer US.

Midkiff, M., Wheeler, J., Baker, E., & Steinberg, K. (2015). The relationship between social media use and stress in college students.

Nann, S., Krauss, J. S., Schober, M., Gloor, P. A., Fischbach, K., & Führes, H. (2010). The Power of Alumni Networks-Success of Start-up Companies Correlates With Online Social Network Structure of Its Founders.***papers.ssrn.com***

Pallant, J. (2005). SPSS survival manual: A step by step guide to using SPSS for windows (version 12). New South Wales, Australia: Allen & Unwin.

Priem, J., & Hemminger, B. (2010). Scientometrics 2.0: Toward new metrics of scholarly impact on the social web [electronic resource]. ***First Monday***, 15(7).

Quinn, K. (2016). Contextual social capital: Linking the contexts of social media use to its outcomes. ***Information, Communication & Society***, 19(5), 582-600.

Raz, O., & Gloor, P. A. (2007). Size really matters—new insights for start-ups' survival. ***Management Science***, 53(2), 169-177.

Rasmussen, J. L., & Dunlap, W. P. (1991). Dealing with nonnormal data: Parametric analysis of transformed data vs nonparametric analysis. ***Educational and psychological measurement***, 51(4), 809-820.

Ries, E. (2011). ***The lean start-up: How today's entrepreneurs use continuous innovation to create radically successful businesses***Random House LLC.

Ross, C., Orr, E. S., Sisic, M., Arseneault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with facebook use. ***Computers in Human Behavior***, 25(2): 578-586.

Ross, D. (2012). Getting results from crowds. ***http://www.crowdsourcing.org/editorial/a-brief-history-of-crowdsourcing-infographic/12532***.
Semrau, T., & Werner, A. (2014). How exactly do network relationships pay off? the effects of network size and relationship quality on access to Start-Up resources. ***Entrepreneurship Theory and Practice***, 38(3), 501-525.
Socialbakers, A. (2015). Formulas revealed: The facebook and twitter engagement rate. http://www.socialbakers.com/blog/467-formulas-revealed-the-facebook-and-twitter-engagement-rate.
Soetanto, D., & Van Geenhuizen, M. (2015). Getting the right balance: University networks' influence on spin-offs' attraction of funding for innovation. ***Technovation***, 36, 26-38.
Song, Y. (2015). From offline social networks to online social networks: Changes in entrepreneurship. ***Informatica Economica***, 19(2).
Stam, W., & Elfring, T. (2008). Entrepreneurial orientation and new venture performance: The moderating role of intra-and extraindustry social capital. ***Academy of Management Journal***, 51(1), 97-111.
Sterne, J. (2010). ***Social media metrics: How to measure and optimize your marketing investment***John Wiley & Sons.
Subrahmanyam, K., Reich, S. M., Waechter, N., & Espinoza, G. (2008). Online and offline social networks: Use of social networking sites by emerging adults. ***Journal of applied developmental psychology***, 29(6), 420-433.
Tan, W.K. & Tan, Y.J. (2012), An exploratory investigation of the investment information search behavior of individual domestic investors", Telematics and Informatics, 29(2), 187-203.
Tatarko, A. and Schmidt, P. (2016). Individual social capital and the implementation of entrepreneurial intentions: The case of Russia, ***Asian Journal of Social Psychology,*** 19, 76 85.
Tichy, N. M., Tushman, M. L., & Fombrun, C. (1979). Social network analysis for organizations. ***Academy of management review***, 4(4), 507-519.
Wasserman, S., & Faust, K. (1994). ***Social network analysis: Methods and applications***Cambridge university press.
Wellman, B., Haase, A. Q., Witte, J., & Hampton, K. (2001). Does the internet increase, decrease, or supplement social capital? social networks, participation, and community commitment. ***American behavioral scientist***, 45(3),436-455.
Witt, P. (2004). Entrepreneurs' networks and the success of start-ups. ***Entrepreneurship & Regional Development***, 16(5), 391-412.
Wu, L. (2007). Entrepreneurial resources, dynamic capabilities and start-up performance of taiwan's high-tech firms. ***Journal of Business research***, 60(5), 549-555.
Xiang, G., Zheng, Z., Wen, M., Hong, J. I., Rosé, C. P., & Liu, C. (2012). ***A supervised approach to predict company acquisition with factual and topic features using profiles and news articles on TechCrunch.*** Paper presented at ICWSM.
Zhang, Y. (2015). The contingent value of social resources: Entrepreneurs' use of debt-financing sources in western china. ***Journal of Business Venturing***, 30(3), 390-406.