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Mining and investigating the factors influencing crowdfunding success

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Published version

SONG, Y., BERGER, R., YOSIPOF, A. and BARNES, B.R. (2019). Mining and investigating the factors influencing crowdfunding success. Technological Forecasting and Social Change, 148, p. 119723.

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Mining and Investigating the Factors Influencing Crowdfunding Success

Abstract

Crowdfunding is an innovative and relatively new financial method that connects entrepreneurs and investors through the Internet. It allows entrepreneurs to raise often small amounts of funds from a large number of investors to finance start-ups. The gaming industry is a suitable market for crowdfunding and has uniquely interesting characteristics that are worthy of exploration. The article examines which factors can influence the success of crowdfunding campaigns in this industry. The study uses principal component analysis, logistic regression and the OneRule method to analyze 9,962 projects between 2009 and 2018. Several attributes, including textual variables are identified that influence the success of crowdfunding campaigns. The findings provide valuable insights for the success surrounding such campaigns and have implications for practice.

Keywords: Crowdfunding, Funding Success Factors, Game Industry, Crowdfunding Reward, Text mining

Introduction

In spite of increased interest in exploring the factors that affect crowdfunding success, their effects within a community setting have been somewhat unexamined (Josefy et al., 2017). The community of investors on which crowdfunding depends upon represents the key source of funding. This article focuses on the community's effect of crowdfunding success in a gaming context. The fundamental uniqueness of crowdfunding is that capital can be obtained from a community of individuals that desire some role in the viability of the start-up and its products. As crowdfunding relies on the crowd, rather than a limited set of professional investors for raising capital, the field of entrepreneurship needs to further understand the dynamics at play in this new form of venture funding, as thousands of ideas go unnoticed and unfunded. Kickstarter reported that slightly less than 36% of projects across all categories had been successfully funded since their inception and 14% never received a single pledge. Understanding the type of factors that draw in potential investors and drive funding success has been a key focus of present research on crowdfunding (Drover et al., 2017).

Research suggests that crowdfunding is characterized by high uncertainty and ambiguity where information asymmetry exists between startups and investors (Zvilichovsky et al., 2013). In contrast to traditional funding, entrepreneurs are able to bypass venture capitalists and banks by raising money directly from individuals (Schwienbacher and Larralde, 2010). A number of online platforms have served as intermediaries between startups and investors. The sum of money raised via crowdfunding in 2016 reached 738.9 million U.S. dollars[1]. According to statistics presented by the Entertainment Software Association (ESA), more than 150 million Americans play video games and 63% of U.S. households play such games at least 3 hours or more per week. Kickstarter is a crowdfunding platform that was founded in 2009 and has been using AON as its reward model. Kickstarter is the largest crowdfunding platform in the world, hosting thousands of projects. Such projects can be divided into fifteen categories, which include technology, games, film and music[2]. Kickstarter is also thought to be the most widely known crowdfunding platform for entrepreneurs, investors and researchers. Several scholars have

[1] https://www.statista.com/topics/1283/crowdfunding/

[2] https://www.kickstarter.com/

conducted research into crowdfunding using Kickstarter as a platform (Agrawal et al. 2014; Belleflamme et al. 2014; Cha, 2017; Mollick, 2014; Smith, 2015).

Crowdsourcing refers to how one obtains ideas, feedback and solutions from the crowd to develop corporate activities (Kleemann et al., 2008). Crowdfunding is the most popular type of crowdsourcing and involves raising the needed capital to finance a project or business (Ahlers et al., 2015). It has been referred to by academics as a wide plea for providing funds in the form of a donation in exchange for a product in the future, or another form of reward that supports the start-up (Belleflamme et al., 2014). One benefit for raising finance through crowdfunding is to avoid incorporating debt or control from external shareholders. In crowdfunding, individuals act as investors, they often give inspiration and in some cases become consumers, advisers and marketers through providing positive word of mouth (WOM) referrals (Ordanini et al., 2011).

Mollick (2014) suggests four different crowdfunding models; the patronage model; the lending model; the reward model; and the equity model. In the computer game industry, the latter two are mostly used. This study focuses on the reward model, since this is perceived as the most prominent model and best fits the computer game industry, where investors receive a reward for supporting a project. In contrast, equity based crowdfunding is limited as it only represents a very small proportion of the crowdfunding market relating to qualified investors (Mollick and Kuppuswamy, 2014). Rewards cannot relate to a share of profits, an interest rate, or anything else that may be seen as a transaction involving an offer of equity or a loan. The act of investing through a crowdfunding platform thus cannot be viewed as a pure form of economic exchange where goods are given in exchange for money (Zvilichovsky et al., 2013).

The marketing environment of the computer game industry has changed dramatically over the past 15 years (Agrawal et al., 2014). The advent of the Internet, digitalization and increased connectivity has made the exchange of computer games easier than ever before (Choi et al., 2007). This has generated extraordinary threats to the computer game industry, but it has also opened new possibilities for innovation and change. New technologies have resulted in the unprecedented growth of the computer on-line game industry based on global peer to peer players (P2P). Several new channels of game promotion and distribution have emerged. They have changed the value chain completely and new ways of organizing relationships between manufacturers, distributors and game players have emerged (Baym and Burnett, 2009; Choi and

Berger, 2009). Constantinides and Fountain (2008) claim that this is the nature of user-controlled Web 2.0, where users are essential contributors, which leads to the migration of market power from producers to consumers and from traditional mass media to greater personalization. Although the literature on computer game marketing analyzes these processes in detail, relatively little attention has been paid to the problem of financing the production of such games, and what particularly makes some succeed and other's fail (Galuszka and Bystrov, 2014; Song and Berger, 2017).

The rapid evolution of digital media, as well as emerging e-commerce opportunities are challenging existing rules of the game in financing and marketing such products (Berger, 2018). Online gaming is one of the most profitable types of business on the Internet (Chang et al., 2011). In the last decade, research on online games has steadily increased. Some researchers suggest that certain personality traits of individuals significantly influence the motivation for playing online games (Davidson and Poor, 2016). Today, online game companies are often able to design effective virtual environments to stimulate and retain consumers, due to the various advances in information technology. The increasing scale and complexity of projects also enhances development costs. Various industry accounts indicate that costs have risen from a few hundred thousand dollars per game about 10 years ago, to millions of dollars for a high-quality game today. However, few researchers have investigated the impact of virtual contact on consumers' intention to invest in online games (Courtney et al., 2017). This is a gap that this study attempts to fill.

Traditional funding mechanisms, such as bank loans and venture capital funds tend not to be offered to early stage start-ups, as banks and capital venture financers generally search for more mature and less risky ventures (Schwienbacher and Larralde, 2010). Such investors are somewhat passive, as they tend not to be interested in the product but are looking for a return on investment. Crowdfunding represents a novel and attractive alternative for entrepreneurs to generate funding without having to use traditional sources. In addition, investors are often potential experts and customers who may also assist in the production and marketing of such computer P2P games (Mollick, 2014). It may provide a potentially transformative experience, allowing start-ups the opportunity to raise funds from a greater scope of investors, which in the future, they may pledge further funds and even become consumers. Crowdfunding allows for the

democratization of funding, potentially making it borderless and less constrained (Mollick and Robb, 2016).

Most studies covering the dynamics of crowdfunding do not distinguish between industries (Balboni et al., 2014; Mollick, 2014). Data reveals that the gaming industry ranks number one for funds raised and fundraising success, making it an important industry worthy of a specific study (Xiao et al., 2014). With the emerging trend of crowdfunding, the gaming industry has experienced a significant boost (Chang et al., 2011). The industry is well positioned to leverage crowdfunding advantages compared with other industries. The gaming industry is unique in so much as it is based on external networks that can provide significant returns. Crowdfunding provides a mechanism for establishing a large customer base (Berger, 2018), it can also promote customer loyalty, and stimulate interest in new projects at early phases of their development (Mollick, 2014). For example, the game console provider Pebble and Ouya had success in raising funds through the Kickstarter platform which led other developers to write applications for this console even before it was launched. This provided the company with a unique competitive advantage. Press coverage also tends to follow crowdfunding campaigns that surpass their funding targets, which can also benefit entrepreneurs through increasing their probability of success.

While some have argued that crowdfunding is borderless and that the entire world is a target audience for funding, this may not necessarily be true (Galuszka and Bystrov, 2014). It is claimed that every funding proposal has a relevant audience, a community of interested people who in one way or another benefit from or identify with a given venture. This community may be defined by a specific geographic region, however in the P2P computer game industry, the type of product, certain personal interests in a technology, or a particular function may be a better descriptor relating to the target group. Thus, it is reasonable to expect that investors in crowdfunding contexts will invest in projects that are compatible with their own collective interests (Sharir and Lerner, 2006). Hence the importance of creating large social networks in P2P computer games crowdfunding to leverage their success (Choi and Berger, 2009).

Crowdfunding investors enjoy getting involved in the innovation process as it is of interest to them (André et al., 2017). They have the ability to control some of the outcomes of the solution. Many backers are interested in participating due to the social interaction experience.

Apart from gratitude and the personal feeling of satisfaction from investing in a specific project, investors often do not get anything else in return. As a result, entrepreneurs frequently need to create greater empathy and initiate a craving desire among potential investors, in order to project positive word of mouth recognition. For example, in 2012, Double Fine Productions launched an astonishing campaign for their video game, Broken Age. They successfully raised $3.45 million from more than 87,000 investors in a single month. This was a much higher amount than the original pledge of $400,000. Double Fine Productions were one of the earliest game developers tapping into the crowdfunding platform and was the highest backed crowdfunding project ever in the category of video games. One reason for their success can be attributed to the fact that their investors were also their loyal clients, which led to a critical mass of users.

In order to gain further insights into crowdfunding, the main objective of this study is to investigate the factors influencing crowdfunding campaign success within a gaming industry context. To achieve this, two sets of variables were considered i.e., control variables extracted and calculated from the Kickstarter data base and textual variables taken from individual project names. In particular, the study aims to use data mining to analyze the games dataset and identify variables that have a significant influence on project outcomes. The study also intends to discover those significant textual variables that have a positive and negative influence on project outcomes, resulting in words and phrases that can enhance or reduce the likelihood that a project will be successful.

Literature Review

Crowdfunding is interdisciplinary in nature, being at the intersection of finance, economics, management, sociology and information systems. Business linkages and social networks are significant channels through which firms can access extra and often complementary assets (Chung et al., 2000; Hoang and Antoncic, 2003; Baum and Silverman, 2004). Social networks can offer access to valued information. According to Granovetter (1983), this inclines to be more valuable than information retrieved through formal networks and can help to build trust. Social networks can help improve a startup’s reputation or legitimacy and may function as a signal of quality (Hoang and Antoncic, 2003; Baum and Silverman, 2004; Berger and Choi, 2014). These potential benefits are particularly crucial during the early stages of a startup.

As a result of knowledge asymmetry, investors can mainly judge a project by observing prior contributions and information conveyed from previous investors. Therefore, the ability to portray positive signals through a platform are useful because they spread information beyond the circle of one's own acquaintances and more significantly, they can prompt reciprocity through a sense of perceived commitment (Coleman, 1990). Although both initial capital and initial investors facilitate observational learning, they can also generate positive word of mouth (André et al., 2017).

Investors often favor taking risks when they recognize a set of imaginable events and probabilities, instead of having vague choices. Entrepreneurs must therefore signal the unobservable characteristics of their venture as a way to reduce ambiguity for potential investors. Entrepreneurs have to effectively promote the quality and benefits of their projects in order to obtain finance. Researchers using signaling theory have explained which types of information, i.e., managerial characteristics, the presence of potential investors and founder involvement that lead investors to finance start-ups (Ahlstrom and Bruton, 2006; Schwienbacher, 2007). There is, however, little research relating to the signaling of startup ventures surrounding small investors.

Startups funded by crowdfunding platforms are often underdeveloped at the time they are presented on a crowdfunding platform. Looking at crowdfunding platforms, it is instantly apparent that early investors offer feedback and suggestions that entrepreneurs use to adapt their offering during a campaign. This feedback, based on signaling theory, allows entrepreneurs to anticipate problems, to know their customers' preferences, and to meet the needs of a broader audience leading to higher customer engagement and loyalty. Research by Evrenk and Sher (2015) found that people tend to go with the flow, a kind of network bandwagon effect. For crowdfunding entrepreneurs, it would imply that the more investors a project has, the more that others will be attracted to join as they perceive the project to be trustworthy and credible. The mechanisms of this process are embedded in the economic theory of network externalities and success when a project achieves a critical mass of investors, often referred to as the "Tipping Point" (Shankar and Bayus, 2003).

Trust is an important factor relating to conditions of uncertainty or risk and it has not been adequately researched in the crowdfunding literature (Chang et al., 2011; Galuszka and Bystrov, 2014; Xiao et al., 2014; Song & Berger, 2017). Trust has a direct impact on investment

intention and is fundamental to crowdfunding (Saxton and Wang, 2014; Wheat et al., 2013). It signals that investors believe that the start-up has the ability to succeed and achieve desired results. High levels of trust were shown to be positively correlated with consumer loyalty and increase customers' willingness to share personal information required for buying the startup's products (Sichtmann, 2007). To gain trust, the start-up has to deliver good and reliable information to potential investors. The relationships that form successful social networks are ones that are built overtime, rather than through one off encounters (Hobbs et al., 2016).

Entrepreneurship is an economic phenomenon embedded in a social context (Berger, 2018). It is facilitated or inhibited by people's positions in social networks. Therefore, for entrepreneurs to succeed in their start-ups, developing social networks is an essential prerequisite. Network externalities is the term used by economists to describe the attractiveness of networks to potential users. Such effects occur when the value that a consumer receives from a product is affected by whether other consumers are using the same product i.e., consumers become members of the same network (Choi et al., 2007; Choi and Berger, 2010). Joining a social network is beneficial because the value of membership to one user is positively influenced when one more user joins and enlarges the social network. Such markets are therefore said to exhibit "network effects," or "network externalities" (Katz and Shapiro, 1994). Network effects are a significant competitive element in markets where, for end-users, the value of the main product strongly depends on the size of the user base, such as P2P computer games. The social benefits of one additional user joining the social network consist of benefits that amass to others in the social network. This forms a bandwagon effect that can bring about increasing returns to those in the network. It is where consumers rush to adopt a new technology that they expect will become dominant, based on the consumption of others (Katz and Shapiro, 1992, Farrell and Saloner, 1985).

The economic theory of network externalities illustrates that the community has a crucial impact, where early adopters trigger other adopters over time (Arthur, 1989). This phenomenon has been documented in both the off-line and on-line world (Chang et al., 2011; Duan et al., 2009; Oh and Jeon, 2007; Zhang and Liu, 2012). It is suggested here that the P2P game industry is no exception. For example, the more players in a P2P computer game, the more people one

can play and interact with. This is a founding block of a P2P game's success, which built on the number of players one can interact with both in the on and off – line world.

While a consumer of a product such as food may gain little value if others also consume it, users of goods that have network externalities gain value if they become widely adopted (Choi et al., 2007). For example, if customers think a specific P2P computer game is going to lead in its category, they may be prepared to pay more. Products derived from knowledge are generally found to obey the "law" of network externalities, i.e. as the number of users increase, the benefits to each increase exponentially. As computer games are digital services, they have a corresponding theoretical marginal cost of zero (Gallaugher and Wang, 2002). The economics of negligible marginal cost, sanction software startup companies to leverage strategies based on network externalities to a greater extent than vendors of conventional goods with higher marginal costs (Katz and Shapiro, 1994).

When competing firms have incompatible and proprietary products, such as computer games, it is claimed that a competitive advantage accrues to the firm with the largest customer network (Katz and Shapiro, 1985). Once a particular product technology gains any small lead over competing technologies in terms of its customer network size, there is a tendency for the product with the larger network base of users to become more adopted (Arthur, 1996). As a result of strong positive-feedback from the market, such products are especially prone to "tipping," which is the inclination of one product to pull away from its competitors in reputation once it reaches a critical point (Katz and Shapiro, 1994). The tipping point, we call critical mass is the point of increasing returns to become a member of the network. It is argued that there is a threshold above which the firm will gain a first-mover advantage, and this threshold is a function of customer preferences, network effects, switching costs and learning costs of the specific computer game called the critical mass point. A computer game that is adopted earlier than others may accrue increasing returns of adoption that allow it to be improved, as well as for complementary products to be developed faster than competing games (Schilling, 2002).

Methods

In order to meet the research objectives, a knowledge discovery workflow was developed (Figure 1). The process is divided into four main sections: (1) Downloading and cleaning the database; (2) Variable selection; (3) Data analysis consisting of data visualization, logistic regression and OneRule, (4) as well as evaluating the data analysis to extract knowledge.

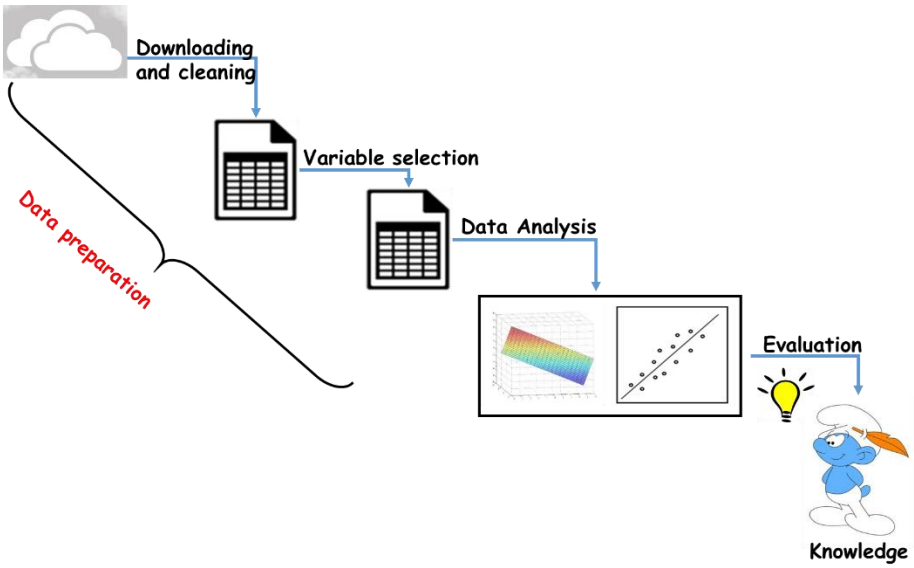

Figure 1: Knowledge discovery workflow

Data base: Downloading and cleaning

The full Kickstarter database was downloaded from Web Robots (https://webrobots.io/kickstarter-datasets/). Web Robots gathers data from all ongoing projects on the Kickstarter platform. All the projects from the full Kickstarter database under the games category were selected, and we removed all canceled and active projects. This resulted in a data of 10,124 game projects over a nine-year period between 2009 - 2018. Following the study of Mollick (2014) several additional projects were excluded from the analysis, i.e., projects with a funding goal of less than $100 and projects with a funding goal above $10,000,000. Such projects were considered to be outliers. This resulted in a further 162 projects that were excluded

from the data set. Finally, the Kickstarter games data set consisted of 9,962 projects, 6,024 successful projects and 3,938 failed projects.

Variable selection

Each project was characterized by one dependent variable, the project outcome (successful or failed project), and 36 independent variables. The 36 independent variables were extracted from two sources. The first source consisted of ten control variables provided or calculated from the Kickstarter database is presented in Table 1. The second source was text mining variables extracted from the start-up project names. Meaning the names of the projects were text mined for frequent phrases and words. The project names were extracted from the Kickstarter database and all text was converted to lowercase and tokenize (i.e. break the text into individual linguistic units). 855 unique phrases and words were found. Any phrase or word which occurred less than 100 times in the text (except the words *iPhone* and *Xbox*) were removed as it was intended to include only general used words and phrases. This procedure led to a total of 26 textual variables presented in Table 2.

Table 1: Control variables extracted from the Kickstarter database and their descriptive statistics.

Variable	Description	Range	Mean	SD
Investors	The number of individual funders supporting the project	0-87,142	548.2	2,800.1
Goal	The amount of money entrepreneurs seek to raise using crowdfunding.	100-9,000,000	30,289.9	181,228.67
Duration	The number of days during which the project runs	1-91	32.5	10.5
Year	The year a project launched	2009-2018	2014.5	1.9
Launched Day	The day of the week a project launched	1-7	4	1.7
Deadline Day	The day of the week a project ended	1-7	4	2
Launched Date	The date a project launched	29/4/2009-2/10/2018	----------	
Deadline Date	The date a project ended	15/6/2009-17/10/2018	----------	
			Frequency	
Country	A dummy variable to record the	0-1	0: 2,602 projects	

	country of the project. Zero for the non-US project, One for US project		(26.1%) 1: 7,360 projects (73.9%)
Staff pick	A dummy variable to record whether the project has been picked by the staff (zero-not picked, one-picked).	0-1	0: 8,258 project (82.9%) 1: 1,704 project (17.1%)

Table 2: Independent text mining variables extracted from the Kickstarter projects names and their descriptive statistics*.

Variable	Range	Mean	SD
Card	0-2	0.2	0.4
Game	0-3	0.2	0.4
Playing	0-2	0.1	0.3
Role playing game (RPG)	0-2	0.04	0.2
Deck	0-2	0.03	0.2
Mobile	0-2	0.02	0.2
Adventure	0-2	0.02	0.1
New	0-2	0.02	0.1
Gaming	0-2	0.02	0.1
App	0-1	0.02	0.1
World	0-2	0.02	0.1
Dice	0-4	0.02	0.1
Fantasy	0-2	0.01	0.1
Android	0-1	0.01	0.1
Board	0-1	0.01	0.1
Ios	0-1	0.01	0.1
Project	0-1	0.01	0.1
Escape	0-2	0.01	0.1
Video	0-2	0.01	0.1
Visual	0-1	0.01	0.1
Novel	0-1	0.01	0.1
Puzzle	0-2	0.01	0.1
Fun	0-1	0.01	0.1
Zombie	0-2	0.01	0.1
iPhone	0-1	0.01	0.1
Xbox	0-2	0.01	0.05

*Each variable presents the number of occurrences relating to the word / phrase.

Data Analysis: Data Visualization- Principal Components Analysis (PCA)

Data visualization provides an intuitive understanding of the overall data structure including the formation of clusters and the identification of outliers (Kaspi et al., 2018; Yosipof et al., 2018, 2016 & 2015). The main problem of visualization of high dimensional data concerns the data representation in 2D or 3D with minimal loss of information. To cope with this problem, dimensionality reduction methods have been developed. Dimensionality reduction aims to preserve as much of the significant structure of the high-dimensional data as possible in the low-dimensional map.

A common technique for data visualization by dimensionality reduction is Principal Components Analysis (PCA) (Jolliffe, 2002). PCA reduces the dimensionality of a data set, yet retains as much as possible of the original variance. This reduction is achieved by transforming the original variables into a new set of orthogonal variables called Principal Components (PCs). PCs are typically produced in an ordered manner so that the first PC retains the largest portion of the variance of the original set, while subsequent PCs retain increasingly smaller portions not accounted for by previous PCs.

Data analysis and Classification Methods

In order to analyze the dataset, two data analyses and classification methods were used, namely logistic regression and OneRule.

Logistic regression is a type of analysis where the dependent variable is binary (or binomial). The model is simply a non-linear transformation of linear regression. The result is an equation which includes the impact of each variable on the odds ratio of the observed event of interest. The advantage of using a logistic regression approach is that it can be used both for statistical analysis and for classification and prediction of the binary dependent variable. In this study, logistic regression was used to analyze the research objective by finding significant predictors (from the 36 independent variables presented in Tables 1 and 2) to the project outcome i.e., failed or successful projects.

OneRule(s) (oneR) is a machine learning algorithm which provides rules that classify an object on the basis of a single attribute. OneR is a classification algorithm that consists of two

main stages. The first generates rules for each attribute in the data and the second selects the rules of one of the attributes with the smallest total error as its OneR model (Holte, 1993). OneR is based on simple association rules. It involves just one attribute and works well for classification and prediction with real-world data. In this study, the classification variable was the project outcome (failed or successful project) and the independent attributes were the 36 key variables presented in Tables 1 and 2. The resulting OneR model not only can reveal the most important attribute for the project outcome but can also reveal hidden patterns in the data i.e., knowledge discovery by providing classification rules based on the key attribute.

Classification Models: Prediction Statistics Evaluation

In all cases, classification predictions were evaluated using the corrected classification rate (CCR), sensitivity and specificity (equations 1-3). Where sensitivity reflects the percentage of truly positive *e.g.*, successful projects being predicted by the model (equation 2), and specificity is the percentage of truly negative *e.g.*, failed projects being predicted (equation 3).

$$CCR = \frac{1}{2}\left(\frac{T_N}{N_N} + \frac{T_P}{N_P}\right) \quad (1)$$

$$Sensitivity = \frac{T_P}{T_P + F_N} \quad (2)$$

$$Specificity = \frac{T_N}{T_N + F_P} \quad (3)$$

Where T_N and T_P represent the number of true negative *e.g.*, failed projects and true positive *e.g.*, successful project predictions, respectively. N_N and N_P represent the total number of the two classes, and F_N and F_P represent the number of false negative and false positive predictions, respectively.

Results

The first step of the data analysis considered the visualization of the Kickstarter game dataset. Each project was characterized by 36 independent variables that formed the feature space. In this space each dimension corresponded to one feature i.e., independent variables, resulting in 36 dimensions (36D). In order to visualize the space, the data set was subjected to PCA. In this

analysis, the original 36D space was reduced into a 3D representation with three principal components (PCs) that explained the highest variance of the original features space. The resulting PCA plot for the Kickstarter game dataset is presented in Figure 2A. The PCA plot (Figure 2A) presents the distribution of the dataset and is colored according to the classification of each project. Blue circles for successful projects and red circles for failed projects. Interestingly, two clusters are clearly observable in the PCA plot and can be seen in Figure 2B. Figure 2B presents the same PCA plot as Figure 2A, but is colored according to the two clusters observed, black circles (cluster 0) for the bigger cluster and red circles (cluster 1) for the smaller cluster. Cluster 0 contains 9,836 projects and is considered as the bulk of the data set and cluster 1 contains 126 projects that are 1.3% of the full data set and can therefore be considered as an outlier. Outliers are defined as objects that appear to deviate markedly from other members of the sample in which it occurs (Barnett & Lewis, 1994). More importantly, outliers may point to a rare behavior that needs to be investigated separately, and may potentially be of great interest for further research and will therefore be further evaluated (Nahum et al., 2015; Yosipof and Senderowitz, 2015).

Evaluation of the outlier cluster (cluster 1) indicates that most of the projects were successful (121 projects 96% and only 5 projects failed 4% out of the 126 projects identified in the cluster). To reveal the differences between the two clusters, two variables were found that were unique to the outlier cluster i.e., the text mining variables - *visual* and *novel*. This suggests that most of the project name outlier clusters contain the word *visual* and/or the word *novel* while none of the names of the projects of the bulk cluster included these words. In order to statistically test this finding, the independent sample *t*-test was used and a significant difference between the bulk (cluster 0) and the outlier cluster (cluster 1) was found for the variable *visual* ($t(125) = -42.9$, p-value<0.001) and for the variable *novel* ($t(125) = -31.6$, p-value<0.001). Further analysis of the two variables found that out of the 126 projects in the outlier cluster, 118 of them listed the word *visual* and only 8 did not, and 112 projects included the word *novel* and only 14 did not. In addition, 105 projects out of the 126 projects in the outlier cluster had the words *novel* and *visual* together. Table 3 provides an analysis of the two variables as a function of the outcome of the projects for the outlier cluster. The results indicate that 95.8% of the projects had the word *visual* and 98.2% of the projects had the word *novel* were successful projects. Also,

98.1% of the projects that had both the words *visual* and *novel* were successful. Based on the outlier cluster analysis, the data revealed that using the words *visual* and/or *novel* within a project name had a significant effect on funding success. This suggests that including the words *visual* and/or *novel* in the project name make it more likely for a game project to achieve success.

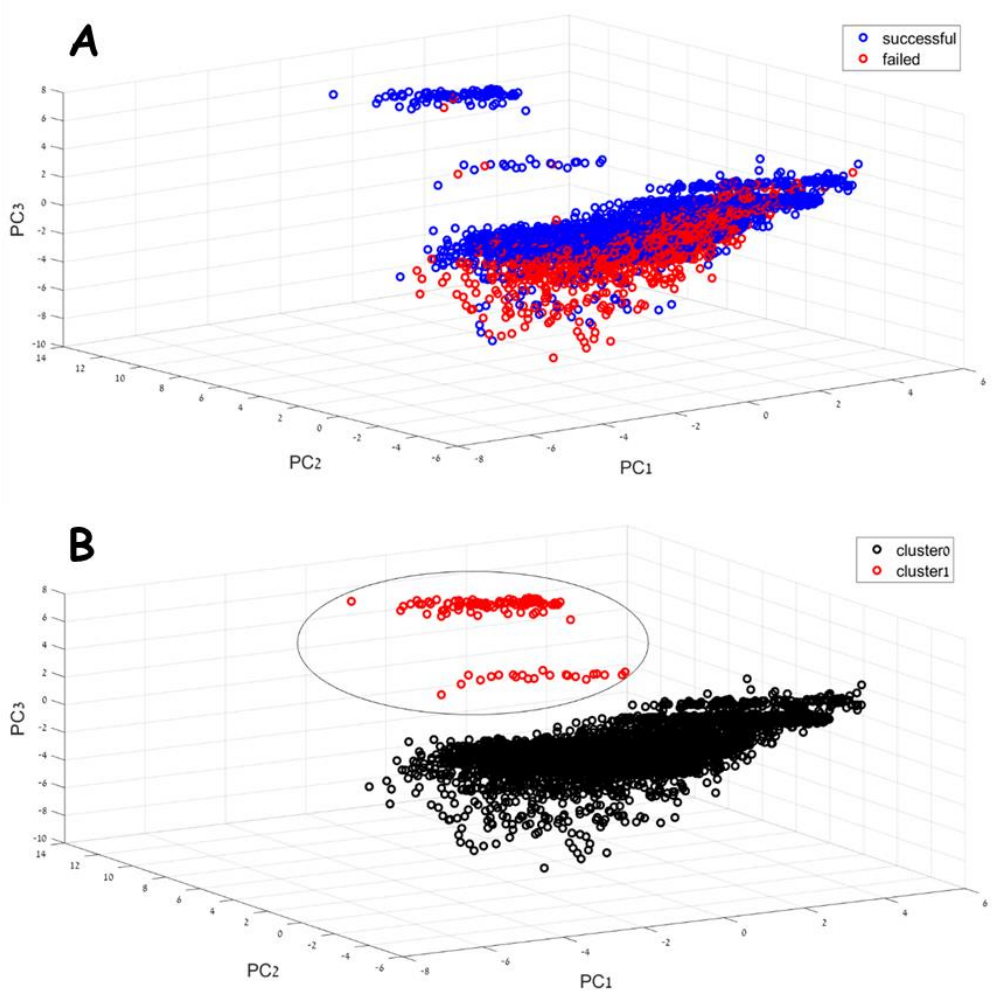

Figure 2: PCA plots for the Kickstarter game dataset: (A) The PCA plot colored according to the classification of each project. Blue circles successful projects and red circles failed projects; (B) The PCA plot colored according to the two clusters observed. Black circles cluster 0 (bulk cluster) and red circles cluster 1 (outlier cluster).

Table 3: Analysis of the text variables "visual" and "novel". N refers to the number of projects that the variable occurs in the outlier cluster.

Variable	N	Successful Projects		Failed Projects	
Visual	118	113	95.8%	5	4.2%
Novel	112	110	98.2%	2	1.8%
Visual + Novel	105	103	98.1%	2	1.9%

The second step of the data analysis used logistic regression to identify the significant predictor variables. In this research, Firth's penalized likelihood method was used to guard against collinearity and sparsity. A stepwise selection with backward elimination process was adopted to derive the final model. The model found collinearity with the variable *Deadline date,* and this variable was therefore excluded. The overall performance of the stepwise logistic regression according to the CCR (Table 7) is 91% with a specificity of 93% and a sensitivity of 89%. Tables 4 and 5 present the statistically significant predictors of the logistic regression model. Table 4 presents the nine significant variables that positively correlated with project outcome, six text variables: *Novel, Board, Role playing game, Fantasy, Adventure* and *Dice* and another three control variables: *Investors*, *Year* and *Staff pick.* Table 5 presents the nine significant variables negative correlated to project outcome, six text variables: *iPhone, App, Playing, Android, Mobile* and *Deck* and another three control variables: *Duration, Launched date*, and *Goal.*

The results indicate that the number of *investors* was found to be positive and significant (β =0.03, p-value<0.001) and are therefore strongly associated with success, meaning that a higher number of investors positively influences funding success. The *Staff pick* variable was found to be positive and significant (β =0.39, p-value<0.05) therefore projects that were selected by staff, positively influences funding success. In addition, *Year* was found to be positive and significant (β =0.25, p-value<0.05), suggesting that those which started in more recent years are more likely to succeed. Similarly, the *Duration* of the project was found to be negative and significant (β =-0.01, p-value<0.001), signaling that a longer duration is associated with failed projects. The project *goal* was found to be negative and significant (β =-0.0001, p-value<0.001) and is therefore associated with unsuccessful projects, suggesting that a higher funding goal

negatively influences funding success. In addition, the project *Launched Date* was found to be negative and significant (β =-0.001, p-value<0.01).

Further analysis of the significant text variables as a function of the outcome of the projects is presented in Table 6. The results indicate for the positive significant variables, that 75.2% and 88.3% of the projects contained the word *Fantasy* and the phrase *Role playing game* respectively were successful projects. Moreover, 92.3% of them including the words *Fantasy* and the phrase *Role playing game* together were successful. In addition, 85.4%, 85.7% and 79.2% of the projects used the words, *Board*, *Dice* and *Adventure* respectively, which were found to be successful projects. On the other hand, for negative significant variables, 87.6% and 79.1% of projects included the word *iPhone* and *Android* respectively failed to achieve the project goal. Moreover, 94.1% of the projects using the words *iPhone* and *Android* together failed. In addition, 87.8% and 81.7% of the projects that used the words *App* and *Mobile* failed.

The final data analysis method applied in this study was the OneR algorithm. The full games dataset was assigned to the OneR algorithm. The resulting rule can be seen in equation 4:

$$(4)\ if\ investors \geq 23\ \ then\ successful\ project,\ otherwise\ failed\ project$$

The OneR model was evaluated using a 10-fold cross-validation procedure. The overall performance of OneR according to CCR (Table 7) is 87%, with a specificity of 81% and a sensitivity of 93%. The OneR result indicates that the most important predictor is the number of investors and suggests that 23 investors or more are needed for a successful project.

Table 4: Significant predictors of the project outcome model for a successful project

Variable	β	p-value
Novel	1.74	<0.05
Board	1.46	<0.01
Role playing game (RPG)	1.24	<0.001

Fantasy	0.85	<0.01
Adventure	0.72	<0.05
Dice	0.62	<0.05
Staff pick	0.39	<0.05
Year	0.25	<0.05
Investors	0.03	<0.001

Table 5: Significant predictors of the project outcome model to signal that the project will fail

Variable	**β**	**p-value**
iPhone	-1.44	<0.001
App	-1.2	<0.001
Playing	-1.11	<0.001
Android	-0.92	<0.001
Mobile	-0.86	<0.001
Deck	-0.43	<0.05
Duration	-0.01	<0.001
Launched Date	-0.001	<0.01
Goal	-0.0001	<0.001

Table 6: *Analysis of statistically significant text variables predictors. N refers to the number of projects that the variable occurs in the data set.*

	Variable	N	Successful Projects		Failed Projects	
Text variables (successful projects)	Fantasy	137	103	75.2%	34	24.8%
	Role playing game (RPG)	366	323	88.3%	43	11.7%
	Fantasy+ Role playing game (RPG)	26	24	92.3%	2	7.7%
	Board	137	117	85.4%	20	14.6%

	Dice	147	126	85.7%	21	14.3%
	Adventure	202	160	79.2%	42	20.8%
Text variables (failed projects)	iPhone	89	11	12.4%	78	87.6%
	Android	134	28	20.9%	106	79.1%
	iPhone + Android	17	1	5.9%	16	94.1%
	App	189	23	12.2%	166	87.8%
	Mobile	246	45	18.3%	201	81.7%

Table 7: Classification model statistics

Method	TP	FN	TN	FP	Specificity	Sensitivity	CCR
Logistic regression	5354	670	3654	284	0.93	0.89	0.91
One Rule	5598	426	3190	748	0.81	0.93	0.87

Discussion and Conclusions

While crowdfunding has gained momentum as an alternative source of financing, it presents unique challenges for start-ups. Working directly with people that are not professional investors requires a set of unique skills such as knowledge about consumer marketing and social networks to ensure effective communication (Steinberg, 2012). Many crowdfunding investors make investment decisions based on feelings and not on rigorous financial analysis (Ordanini 2009). Information asymmetry between start-ups and potential investors, creates the need to disclose credible information that potential investors can use to evaluate potential projects. Using crowdfunding platforms and reaching large audiences, demands signaling transparency, openness and trustworthiness. Small investors are likely to lack the financial sophistication and experience of venture capitalists, who are generally highly knowledgeable about valuing start-ups and assessing funding teams and therefore search for signals of quality (Freear et al., 1994). On the other hand, this information may place the company at risk of intellectual property right

theft and lead to negative word of mouth at an early stage. This can hinder the start-up at its most vulnerable stage.

To the best of the authors' knowledge, this article provides one of the first quantitative attempts to identify the factors which affect the success of game category crowdfunding campaigns. This study has analyzed the factors influencing success in the games category on the crowdfunding platform Kickstarter over a period of nine years between 2009-2018 by using different variables including for the first time, text mining names relating to projects. As the crowdfunding market is growing, so is the public perception for alternative financing methods. This study provides investors, entrepreneurs and crowdfunding platforms with a better understanding about the market, particularly within the gaming industry. By learning about what factors have the highest significance for generating success, investors, entrepreneurs and crowdfunding platforms can connect innovation and funding in a more efficient way. This study makes important theoretical and practical contributions and also opens avenues for future research.

Looking at different analyses, it was discovered that inserting the words *visual* and *novel* increases the project's average success from 60% to around 95% - 98% in relation to other similar projects that do not use these words in their titles. Furthermore, inserting the following words were found to increase moderately the success rate of the project: *Fantasy* (75.2%), *Role Playing Game* (88.3%), *Fantasy & Role Playing Game* (92.3%), *Board* (85.4%), *Dive* (85.7%) and *Adventure* (79.2%). It is important to note that inserting the following words can increase a projects failure rate: *iPhone* (87.6%), *Android* (79.1%), *iPhone & Android* (94.1%), *App* (87.8%), and *Mobile* (81.7%). Thus, the text mining research highlights the importance of choosing the appropriate words in the project's title in-order to increase the probability of success.

OneRule and Logistic Regression

Staff pick is a unique feature which Kickstarter uses to help projects become more popular and acquire attraction from investors. It is a reliable variable used in other studies (Xiao et al., 2014). As stated on the Kickstarter website, *"when something sticks out as particularly compelling,*

whether it is a really fun video, creative and well-priced rewards, a great story, or an exciting idea, we make the project a Staff Pick". The benefit of allowing staff to pick it, is that it makes entrepreneurs more compelling to get the attention not only from potential investors but also from journalists and online communities who are considered experts by small investors. Kickstarter frequently select their favorite projects to be featured on the homepage of their website, thus leading to higher visibility. This feature can significantly help projects to attract potential investors. According to Mollick (2014) and this study, being featured by Kickstarter on their homepage increases the chances of success.

In line with Koning and Model (2013), the number of investors had a strong positive correlation on project success, as a larger number of contributors represent a strong signal of project quality and success. Customers are more willing to believe in the choice of others in a stock market context (Kremer and Nautz, 2013) and in purchasing over the Internet (Ye, Cheng, and Fang, 2013). This effect also occurs in the crowdfunding ecosystem, with an increasing number of individuals backing projects, indicating their credibility and feasibility. The finding fits well with the network externalities theory presented in the literature review. It was found that the tipping point for successful projects is 23 investors, which will lead to a cascading effect on other potential investors.

Using Logistic Regression

In line with Mollick's (2014) study, it was found that raising too little or too much capital will result in project failures. As many factors can influence the results of projects, entrepreneurs should select realistic funding goals. The findings also support the work of Kuppuswamy and Bayus (2017), as well as Mollick (2014), as they suggest the longer the duration of the project, the higher the probability of failure. Kickstarter cofounder, Yancey Strickler had previously stressed that more time does not necessarily create more urgency. Instead it makes it easier for investors to procrastinate, and sometimes they forget to return to the project. Interestingly, the study found that projects which had a shorter duration tended to attract more investors to reach the desired funding goal. The launch date was a negative predictor of project success, while the year the project was launched had a positive correlation on a project's probability of success. This means that as time goes by and the newer the projects are, the probability of success increases. This leads one to believe that this could be a useful indicator that the platform is

gaining traction with investors. The more recent the project is, the higher its probability of success.

The results of this study illustrate new opportunities for entrepreneurs in understanding the factors controlling the outcome of computer game projects and provides some guidelines on how to higher the odds that the project will succeed. It is expected that the results will help entrepreneurs to achieve better outcomes in fund raising when using the Kickstarter platform. The findings developed in this study can offer additional value for entrepreneurs and business owners especially in the game industry across the crowdfunding environment. It provides entrepreneurs with insights surrounding the factors of crowdfunding game project success. The recommendations aim to support entrepreneurs or business owners in setting up a reward based crowdfunding game project.

The findings of this study are beneficial for both crowdfunding platforms, such as Kickstarter and entrepreneurs who are searching for new means of funding. In particular, the findings may help to better understand how one can achieve a critical mass of investors leading to a potential bandwagon effect. The biggest benefit for a start-up company in using crowdfunding is the fact that such campaigns do not only help obtain low-cost financing, but they also allow entrepreneurs to raise public awareness and interest before the product or service is launched, which can help to develop a strong user client base (Song and Berger, 2017). In turn, this provides an opportunity to test the market with potential customers, leading to a better fit between users and products, thus generating higher penetration (Schwienbacher and Larralde, 2010). It also removes the geographic barriers of investments and allows a crowd to participate in the creation (Belleflamme et al., 2014). This may also widen market coverage and the probability for success. By analyzing how social capital helps to attract investors one can help increase the success rate of start-up fund raising campaigns.

On a theoretical level, this study contributes to the existing literature by further developing our understanding of which factors have a significant influence on the funding success of crowdfunding projects, especially in the gaming industry. This study contributes to the extant literature surrounding the role of *social capital* in crowdfunding, and more generally on a start-up's ability to raise capital through on-line platforms. Combining the existing literature with empirical analysis, this study was able to develop and test a conceptual model governing the

success factors for reward based crowdfunding projects. The study advances the extant knowledge in several respects. First, it contributes to the nascent crowdfunding literature. It can be clearly seen that Web 2.0 technologies have enabled proponents to broadcast their financing campaigns on the Internet, fueling the rapid diffusion of crowdfunding. In spite of this increasing popularity, academic research on crowdfunding is still at an initial stage. Research that has examined the drivers of campaign success have observed that one's social network serves as a useful predictor of success, in a 'success, breeds success' self-reinforcing pattern. In this article, this idea is taken a step further by offering a comprehensive discussion of the reasons for that pattern, i.e., observational learning, word-of-mouth referrals, along with feedback from investors. Little is known about what drives entrepreneurs to use equity crowdfunding over other financing sources. Perhaps the potential to inspire a large number of investors, with benefits of increasing returns is appealing.

As can be seen, online communities are a major source of marketing potential. Investors can mainly judge a project by observing prior contributions and information conveyed from previous investors. Therefore, the ability to portray positive signals through a platform are useful because they spread information beyond the circle of one's own acquaintances and more significantly. P2P games were found to obey the "law" of network externalities, i.e. as the number of users increase, the benefits to each increase exponentially. As computer games are digital services, they have a corresponding theoretical marginal cost of zero (Gallaugher and Wang, 2002). As a result of strong positive-feedback from the market, such products are especially prone to "tipping," which is the inclination of one product to pull away from its competitors in reputation once it reaches a critical point (Katz and Shapiro, 1994). The tipping point, we call critical mass or mimetic behavior, is the point of increasing returns to become a member of the network. Using OneRule we found that this threshold stands at 23 investors. It is argued that there is a threshold above which the firm will gain a first-mover advantage, and this threshold is a function of customer preferences, network effects, switching costs and learning costs of the specific computer game called the critical mass point.

Therefore, crowdfunding project creators need also to remember that the communities they build around their projects are not only providing the funds, but such individuals may also serve as co-creators, participants, consumers and supporters or advocates. Learning how to use

viral marketing to gain more visibility through the efforts of the community can be a major factor for the success of a campaign. Creating a community of gamers who are excited about the game is not an easy task. But if they are addressed in the right way, they can create a strong network of supporters who are eager to share marketing messages and contribute to the game development process through feedback. It is argued here that reward-based crowdfunding platforms foster reciprocity among their members beyond pure altruism and self-interest. Reciprocal giving is also associated with superior success of such campaigns (André et al., 2017). Reciprocal giving establishes an affective relationship, whereas an economic exchange typically creates no emotional connection between the buyer and the merchant.

Rewards must be based on multiple facets, including the capacity to generate connections and interactions between backers and entrepreneurs. In this sense, far from being anonymous and impersonal, crowdfunding tends to support reciprocal relationships, at least for a significant proportion of backers. Potential backers can have many ambiguities about the legitimacy, quality, completion and success of a video game project on crowdfunding platforms. This study examines how the selection and use of media affect the success of crowdfunding campaigns for video games. A video game combines sensory and motor engagement to create presence. Thus, communicating the quality of a video game through a crowdfunding campaign might be challenging. Presence enables a video game player's mental model to be situated inside the virtual world. Video game developers design vividness and interactivity features to boost their users' sense of involvement and immersion in games.

An area of potential improvement in this field could be to analyze additional categories from the Kickstarter platform, separately and together with the others used here. This analysis may provide fresh insights into the factors influencing each specific category and the global factors affecting all the categories together. Another area for future research could be to analyze other platforms. Since this study focused on a specific crowdfunding platform, testing the finding on different platform contexts with a similar focus could enhance the reliability of the findings. Such research is likely to contribute to knowledge and benefit both practitioners and academics alike, as they grapple with such new and pertinent issues surrounding crowdfunding.

In conclusion this study has investigated the factors influencing Kickstarter campaign success in a gaming industry context. To the best of the authors' knowledge, this is the first time

that a study has used textual variables and text mining in such a context. The study revealed that using the words *novel, visual, adventure, dice, fantasy* and the phrase *role playing game* in the project name had positive effects on project outcome. In contrast, using the words *iPhone, Android, app, mobile, playing* and *deck* in the project name were found to have a negative effect on project outcome. Several control variables, including *staff pick, year of the project, number of investors, project duration, project launch date* and *project goal* were found to be significant predictors of project outcome. It is perceived that these findings will prove useful in helping new entrepreneurs to achieve better results.

Acknowledgement

This paper is supported by National Natural Science Foundation of China (No. 71874068), Youth Foundation of Humanities and Social Sciences, Ministry of Education of China (No. 17YJC790129), Jilin Province Science and Technology Development Plan Project (20180418128FG).

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