



Research article

Analyzing the impact of social capital on US based Kickstarter projects outcome

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ABSTRACT

The essence of this paper is to analyse the ripple effects caused from the intertwining and complex relationship between the relational and structural dimensions of social capital on the US based Kick starter projects' outcomes. This will be measured based on real time data collected from the Kick starter. com in form of 1157 projects organised in the structure of the number of backers, amount of time taken to fund the projects and the converted amount pledged towards the projects, as classified according to various project categories and geographical locations. This research applies qualitative and quantitative statistical analysis methods as well as data mining techniques; k-Nearest Neighbour, Naive Bayes and Decision Tree Algorithms. The results from this research confirm that relational social capital i.e. the number of backers involved in the projects, has significantly strong and positive impact on the converted amount pledged towards a project and the project outcome. This paper also offers a feasible decision-making model that will be used by the entrepreneurs in the future to determine which type of project categories an entrepreneur can choose to host and the project outcome.

1. Introduction

The concept "Crowdfunding" started in 2003 when Brian Camelio a Boston musician and computer programmer launched the "ArtistShare" platform that would allow fellow musicians to seek funding from their fans and wellwishers. The platform later developed into a fundraising forum for film/video and photography projects besides music. The success of this forum lead to the advent of more popular reward-based forums like Indiegogo and Kickstarter in 2008 and 2009 respectively [1].

In comparison to the concept of traditional funding, crowdfunding is much easier and simpler as it brings people who have a common passion together and doesn't involve timely processes of doing extensive and sometimes uncomfortable pitches of the business plan to people who have no idea of what the potential of the project is, or applying for bank loans. The Entrepreneur is also sort of hand held and shown the processes of how to get his/her project successfully funded.

Social capital, as defined by Bhandari et al. [2], is a communal asset in the form of shared norms, values, beliefs, trust, networks, social relations, and institutions that facilitate cooperation and collective action for

mutual benefits. Many scholars have attempted but failed to specifically define the concept of social capital as it is applied in different fields including behavioral sciences as well as economic and sociological studies.

For the purpose of this research, we shall showcase the concept and theory of social capital as a "glue" that bonds and also binds the entrepreneur and the backers in the act of crowdfunding. In our understanding, it is also a catalyst that ensures crowdfunding project success [3, 4, 5].

The main objectives of this research paper are to offer a innovative method of measuring the impact of social capital on US based Kickstarter project outcome and propose an accurate decision making tool that the entrepreneur and backers will use in determining which projects to host and finance based on the project's likelihood of success, given the a fore mentioned crucial factors.

In order, to reach the mentioned primary objectives, the following secondary research objectives will be attained:

- (i) Determine whether an increase in the number of backers translates in an increase in the amount of money pledged towards a

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project and thus positively reflecting on the project outcome. i.e. success.

- (ii) Determine whether the projects geographical location positively influences the number of backers involved in the project.
- (iii) Determine whether a longer time duration of a project positively impacts the amount of money raised in the project.

We develop a feasible Decision Tree and KNN model that will be used by the entrepreneurs in the future to determine which type of project categories an entrepreneur can choose to host and the project outcome based on the mentioned dependent variables.

The Geographical location of a project doesn't directly correlate with the number of backers involved in the said project and the latter 's willingness to be involved. However, if the entrepreneur and the backer are within the same or similar geographical locations, the two are acknowledged to share similar backgrounds in regards to experiences, outlooks, socio-cultural values and possibly interests, in comparison to the ones who are from different locations.

This therefore might positively influence the amount of support an entrepreneur might receive towards his/her project, based on the mentioned structural and relational social capital clout he/she has on the backers as an individual and collectively.

In 2014, Mollick [6] discovered that the backers who share the same geographical area as the entrepreneur, are most likely to be the initial contributors of the project. These initial contributors also share a strong social bond with the entrepreneur as they are family and friends. However, the close friend of a friend or a relative are also considered as friends and this therefore makes it hard not to consider the eventual backers as friends too.

In addition, local Backers appear less responsive to information about the cumulative funds raised by an entrepreneur. However, this distance upshot appeared as an alternative for a social effect. This was largely explained by Backers who were likely to have an offline social relationship with the entrepreneur i.e. ("friends and family"). Regardless of this fact, this social effect did not persist past the first investment, suggesting that it may have been driven by an activity like search but not monitoring [7].

If an entrepreneur has a strong individual and collective antecedent this in turn reflects on the size and "value" of his/her individual and collective social network which then results in both the individual and collective having a "durable" social capital that has been brought about by shared experiences and motivation towards the same objective. Gedajlovic et al. [8] in 2013, noted that positive social capital whether individual or collective, bears significant impact on the individual and collective entrepreneurial outcomes. Many positive outcomes therefore accumulate and result in individual and collective performance outcomes i.e. in this case project outcomes.

Therefore, rather than measure the impact of initial backers on the project outcome, it is simpler to measure the impact of the total number of backers in the project on the project outcome, as a result of the entrepreneur's individual and collective social network performance and overall output also known as the project outcome.

Some scholars consider the value of social capital as trust and measure it using signaling theory by determining the number of mutual friends in the entrepreneur's social media network or alternatively word signaling by assigning weights to specific keywords in the crowdfunding pitch that might positively influence more backers to join a project [9, 10, 11].

This method requires huge data volumes collected over long time periods as an entrepreneur's social network requires time to grow and develop and sometimes, in different circumstances the same or similar wording in different pitches have different weights.

As an alternative, this research paper suggests considering the correlation between the converted amount of money pledged in the project to the number of backers involved as a measurement of trust between the

backer and the entrepreneur; as well as a sign of the backer's faith in the said project. This ultimately determines the project outcome.

Rewards-based projects are known as high risk due to their "All or Nothing" nature. The timeline of a project is between 30 to 60 days, whereby an entrepreneur has to bear in mind that projects lasting 30 days or less have the highest success rates. Some entrepreneurs favor briefer time duration as a result of a lower likelihood of a funding "dead zone" whereby, a project's impetus ascends in the beginning as well as at the end, but can delay during a drawn middle time period. This requires the entrepreneur to find a suitable average between the project's time frame and the backer's attention span.

Funding of new ventures is strongly ascribed to information asymmetry and issues of moral hazards. Therefore, people who are familiar with rewards-based crowdfunding have to decide on whether they can participate in a project based on several key elements including;

- (i) whether the project allows strong emotional content that the entrepreneur and his/her financiers would be able to associate with, individually and or collectively.
- (ii) whether the amount of money to be invested is enough to cover insignificant and ensuing loss, depending on the project outcome and
- (iii) whether the project returns create an exclusive non-monetary benefit that will be shared only among financiers who enhance the social and emotional nature of the project [12].

If an entrepreneur has a strong individual and collective antecedent this in turn reflects on the size and "value" of his/her individual and collective social network which then results in both the individual and collective having a "durable" social capital that has been brought about by shared experiences and motivation towards the same objective. According to Gedajlovic et al. [8] positive social capital whether individual or collective, bears significant impact on the individual and collective entrepreneurial outcomes. Many positive outcomes therefore accumulate and result in individual and collective performance outcomes i.e. in this case project outcomes.

In 2017, Kuppaswamy et al. [13] stated that as Kick-starter projects approach their goal, they receive more backer support, but after the goal is achieved, support drops off abruptly. In the meanwhile, the goal gradient effect is strongest when backer support is likely to have the greatest impact, that is, if the project is nearing its funding deadline, if the project is small, or if the project has limited early support. It seems that people are willing to help others in the crowdfunding community financially, particularly if they believe that their contribution really matters.

In our methodology, we explore kNN, Decision Making Tree and Naïve Bayes Algorithms as they are useful tools which offer feasible decision-making techniques that will be used by the entrepreneurs in the future to determine which type of project categories an entrepreneur can choose to host and the project outcome based on the mentioned dependent variables.

Thereafter our research analysis and conclusion will be drawn based on the a fore mentioned research questions and objectives and in addition, provide insight on how entrepreneurs, backers and crowdfunding platforms can interact better together to provide smooth information asymmetry for better decision making.

2. Literature review

The Literature Review outlines a clear relationship between social capital and crowdfunding, by breaking down social capital into three schools of thought and discussing the research gaps in these schools. Through empirical studies of recent literature, we further explore the application of social capital in crowdfunding as well as possible aspects of future research.

2.1. Crowdfunding defined

According to Dyer et al. [14] crowdfunding is defined as a means of collecting funding (in contributions) through an online platform. On the onset of a business, entrepreneurs are faced with the great challenge of having to raise capital. It would more often than not require having to take loans from the banks, or borrowing from friends, at the cost of having to attach assets as collateral in case the loan doesn't get paid on the agreed time. It is even harder to have to convince the said Investors to fund a new business since they do not share the same ideas and dreams as the entrepreneur.

Some scholars are of the opinion that Crowdfunding projects can range greatly in both goal and magnitude, from small art projects to publishing, technology, filming, photography and even music, to entrepreneurs seeking hundreds of thousands of dollars in seed capital as an alternative to traditional venture capital investment [6, 15].

According to research done by Mollick [6] in 2014, Crowdfunding on the other hand is a very innovative way for funding a variety of new businesses, by making it possible for the Entrepreneurs of for-profit, cultural, or social and welfare projects to request funding from many individuals or companies, often in return for future products or equity. Crowdfunding therefore is a joint effort for many individuals to pool their money and resources together, so as to invest in and support efforts initiated by other people or organizations. The idea that a group of complete strangers getting together to decide to pay for producing and promoting a product, and tolerate the risk, represents an additional step in the evolution of consumers' roles.

2.2. Origin of crowdfunding

Crowdfunding is inspired from micro-financing and crowd sourcing. In 1994, Otero and E. Rhyne [16] referred to micro financing as the government's direct or indirect provision of small-scale financial services of both credits and deposits being provided to people who operate micro enterprises and medium businesses, where goods are produced, recycled, repaired, or traded.

These micro enterprises can also provide services; work for wages or commissions; gain income from renting out small amounts of land, vehicles, draft animals, or machinery and tools; and to other individuals and local groups in developing countries, in both the rural and urban areas in a country. Thus reducing poverty levels in the country as well as increasing employment levels [16].

Some scholars share the opinion that micro finance is the provision of financial services to low income, self-employed and simply as an online, well-circulated problem solving and production model that influences the collective intelligence of online communities, to serve specific organizational goals. This therefore precedes the feature of crowdfunding whereby it's a form of collaboration that involves the public "crowd" in the search of addressing real world problems in the form of an open call [17, 18].

The term crowd-sourcing was first coined by Jeff Howe as an innovative structural form where companies took roles that once were filled by employees and outsourced the work to other individuals or companies by making an open call (advertisement) to online communities. He was one of the first people who recognized crowd sourcing as the online collaboration of people from around the globe regardless of language, ethnicity, background or culture. He further broke down crowd sourcing into four categories namely: crowdfunding, crowd-voting, crowd-creation and crowd-wisdom [10].

2.2.1. Case study of Kickstarter

Figure 1 categorizes crowdfunding projects into four main models, namely: rewards-based funding, donation-based crowdfunding, equity-based crowdfunding and loan-based crowdfunding. In Reward based crowdfunding, the entrepreneurs offer their products or a one on one interaction with the contributors, where the Backers get to experience the product first hand, in return for funding the entrepreneurs can also name the Backer as a contributor in the project. In reference to donation-based crowdfunding, the Backers offer their contributions due to certain emergencies being experienced by the beneficiary of funds. These can be natural disasters, personal emergencies (for example paying hospital bills, education tuition fees etc.) For the purposes of this paper, we shall

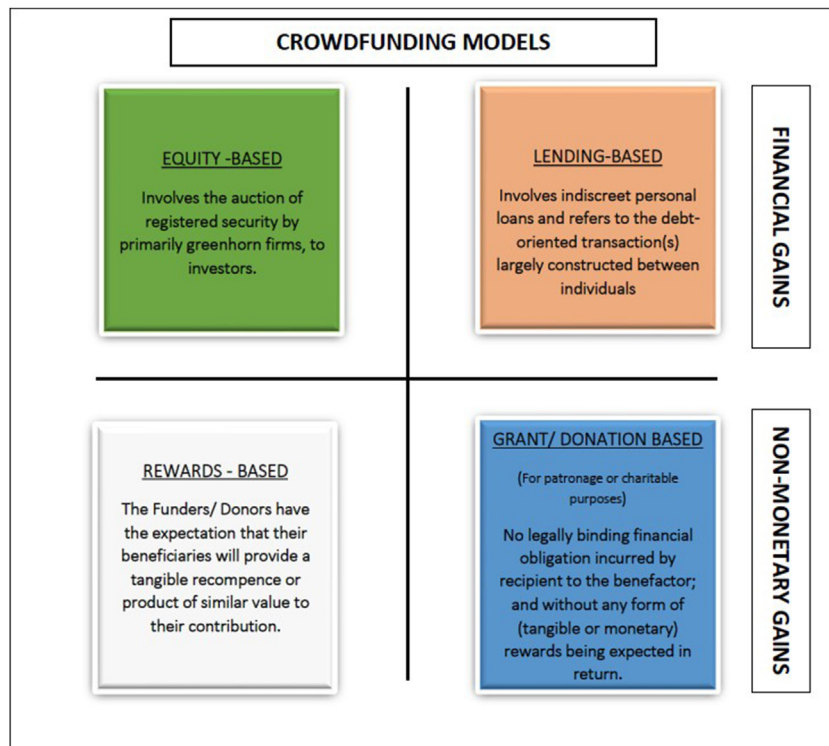


Figure 1. Crowdfunding project models.

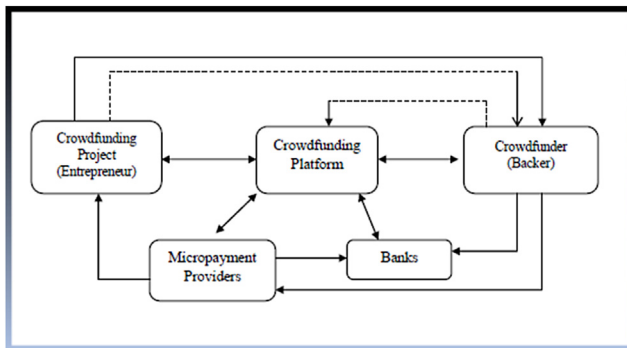


Figure 2. Crowdfunding structure and processes.

focus on Rewards-Based Crowdfunding more specifically, US based Kickstarter.com projects.

As of 2015, one of the most prominent reward-based crowdfunding platforms was Kickstarter.com. The platform is considered one of the world's most famous reward-based crowdfunding platforms. In March 2011 alone, 7 million dollars was pledged towards projects and 2,000 plus projects launched in the same month. This therefore brings the gross amount of money pledged since April 2009 to \$53,107,672. According to their own website, since its launch in 2009 until March 2015 more than 75,000 projects had been funded through Kickstarter (and more than 1.5 billion US dollars been pledged) [19].

By May 2020, a total amount of \$5,009,775,797 had been pledged to Kickstarter projects and 182,414 projects has been classified as successfully funded with a total backer count of 7,940,928 and 5,970,254 being repeat backers. Kickstarter applies the All or Nothing (AON) model of operation whereby the entrepreneurial firms set a fundraising goal. If the goal is reached or over pledged then the campaign receives the capital, if not, then the campaign fails.

2.2.2. Project categories

Kickstarter Projects worldwide are classified into 14 main categories namely art, comics, dance, design, fashion, film and video, food, games, music, photography, publishing, technology, crafts and theatre. Each category has between 7-14 sub categories that further identify the project type.

As the end of May 2020, according to Kickstarter stats website, the top 5 project categories with the highest success rates are Dance (61.70%), Theatre (60.01%), Comics (59.09%), Music (49.98%) and Art (44.26%), respectively. The top 5 successfully funded project categories were Music (31,111 projects), Film and Video (28,002 projects), Games (21,302 projects), Art (17,120 projects) and Publishing (16,516 projects).

At the same time, the total number of unsuccessfully funded projects on Kick-starter was 301,381 significantly higher, and close to double the number of successful projects. The top 5 project categories were Film and Video (46,473 projects), Technology (33,623 projects), Publishing (33,211 projects), Music (31,137 projects) and Games (30,715 projects) in that order since 2011 [20].

In order to grasp the crowdfunding process, as we demonstrated in Figure 2, some terminologies are introduced to show the structure and process of crowdfunding interactions between the internal and external elements of a crowdfunding project.

A crowdfunding platform, which is also referred to as a crowdfunding website, is where an individual or company can create campaigns and pledge funds. A Campaign refers to advertising/calling a project on an online platform to raise funds for a certain amount of time. An Entrepreneur/Creator refers to someone who starts a campaign on a platform. Backers or pl edgers otherwise known as Investors refers to the single or multiple entities that donate money to projects.

A pledge refers to the investment made by a potential investor/pl edger. Funded means a project has reached its funding objective and so

the payment of the amount of money raised is forwarded to the Entrepreneur through the banks. A reward is what investors receive as compensation for their pledge. Perks are the different levels of rewards that backers receive depending on the amount of contributions pledged. Over-funded/Stretch goal happens if a campaign exceeds the initially set financial target, there can be additional goals which add more features to the complete project.

For example, if a music or film project reaches its set goal, the makers can add bonus tracks or additional scenes or effects. However, the downside to this, is that the investors would have high expectations about the project and thus make the project more complicated as the entrepreneur makes the necessary changes to his/her project to meet these expectations.

Project Status is defined as the outcome of a project based on the converted amount of money pledged by the backers, within the stipulated time duration therefore determining whether the project will be live, successful, cancelled or have failed. A live project means a project is still being crowdfunded and the outcome unknown.

Once a project has been declared as successful, the financial intermediaries (banks and micro payment providers like PayPal), exchange information and the project and the Crowfunder exchange rewards and financial transactions between each other and the crowdfunding platform based on the converted pledged amount raised.

2.3. Social capital and crowdfunding

Social Capital has been referred to as the cumulative of the actual or potential resources linked to the possession of a durable network or more or less institutionalized relationships of mutual acquaintance and recognition. It consists of some aspect of social structure, and facilitates certain actions of actors whether individuals and or social/corporate groups within the structure 4, 21.

However, there is a middle line between two social capital theoretical traditions; the first is a functionalist view of social action which is conditioned by social structure and the second, a rational theory which suggests that an actor's goals are determined by utility-maximizing pursuit of his/her self-interest [21]. In 1993, Putnam [22] stated that, social capital refers to the structures of social organizations, consisting of elements such as networks, norms and trust which enable action and cooperation for mutual benefit.

In the advent of the study of crowdfunding, researchers focused on various social capital factors which were said to be significant contributors to the success of Kick-starter projects. These include: The Size of the Entrepreneur's Social Network and how this network impacts the project outcome based on social media marketing i.e. mostly on Facebook and Twitter. A significant factor in social network marketing is the linguistic style used to market the projects which attracts more potential backers and funding to the project 19, 23, 24.

New research findings later on discovered that time and geographical location also played a significant role in crowdfunding success; whereby most successful projects only took 30 days (more or less) to be fully backed and backing increased in the beginning and towards the end of the project's life-cycle. The backers in the beginning of the project life-cycle were identified as domestic backers who shared the same geographical location as the entrepreneur i.e. Friends and Family [7].

Due to the relationship that these backers shared with the entrepreneur, they did not back the project due to initially provided detailed information of the project. They however backed the project due to due diligence brought about the strong bond which they shared with the entrepreneur. This as a result, brought issues of information asymmetry as it became difficult for these backers to convince other potential backers in their social circle to fund the project [12, 25, 26].

As for the backers who later joined a crowdfunding project it was discovered that they made the decision to back the project as a result of detailed information they received about the project or they also shared some history with the entrepreneur in regards to working together on a

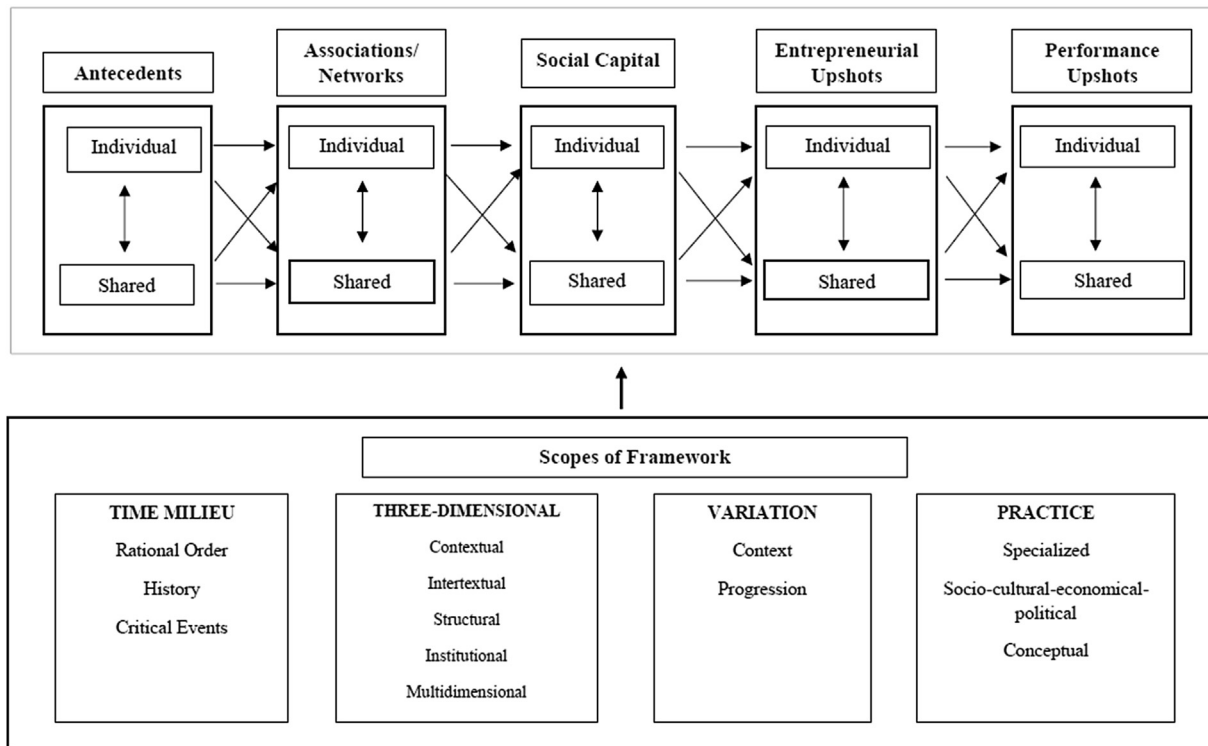


Figure 3. A representation model of social capital and entrepreneurship.

previous project. These backers were defined as repeat backers who could also be domestically and internationally located [27].

In order to solve the issue of information asymmetry and rewards sharing in rewards-based crowdfunding as well as the impact of social capital on Kick-starter project outcome, social capital theory is applied as a bridge and bond that interconnects the Entrepreneur and the backers through various means as we demonstrated in Figure 3.

Social capital conceptualized is dynamic in nature and therefore in different dimensions of context produces different outputs. Some scholars for instance have noted that the positive consequence of social capital results in individual and collective expansion and growth. On the other hand, the negative impact of it results in insecurity, loss of resources and sometimes corruption within the structure [28].

In reference to crowdfunding, positive social capital means the successful outcome of the project, whereas depending on how negative the social capital is, the outcome of a project can at worst, fail, or be cancelled or suspended; meaning that the funding goal of the project has not been achieved. We shall further discuss the three dimensions of social capital which lead to crowdfunding success, namely: Structural, Relational and Conceptual dimensions [29].

2.3.1. Structural social capital

This dimension of social capital refers to the all-inclusive pattern by which individuals are entrenched in social networks. It consists of the entrepreneurs' and backers' social network ties which aids in the reduction of information asymmetries, un-certainty as well as increases group collaboration. This is supported by emerging literature which proves that the entrepreneurs' social network size and the mixture of the influence of different social networks ties on the performance of a project are measured as the factors of crowdfunding success [13, 30, 31].

On the onset of research on crowdfunding, there was emphasis in regards to finding the determinants of crowdfunding success [32, 33]. Nesta [34] in 2014 conducted a survey which suggested that two-thirds of UK backers regarded their social network as a significant element that contributed to the success of crowdfunding projects. Due to the huge uncertainty in crowdfunding campaigns, a study by Ahlers et al. [35] in

2012 discovered that start-ups were required to signal their accurate value to small investors by applying signal theory to crowdfunding research and that the entrepreneurs' social networks were an inflated signal.

Research conducted in a similar manner by a significant number of researchers emphasized on the role of social networks in crowdfunding by putting forward the notion that social networks had the ability to alleviate information asymmetry, aid entrepreneurs develop their mutual identity as well as enable the entrepreneurs' access to more resources. They concluded that the entrepreneurs' social network size had a positive impact on Kick-starter project success [36, 37, 38].

Some crowdfunding studies also considered social capital as a control variable and established a positive relationship between social network and crowdfunding success [6]. However, in 2012, Ahlers et al. [35] chose factors different from the number of online friends and found dissimilar effects. Their research applied the share of non-executive directors on ventures' boards to measure social networks and found that social networks have no influence on crowdfunding success.

On the other hand, in 2016, Chen et al. [39] measured the number of community members on the lending crowdfunding platform derived from the social network size on The Prosper Marketplace. The result demonstrated that lesser group cohesion was derived from larger group network size and is negatively linked with the project's performance.

2.3.2. Relational social capital

Relational social capital refers to the type of individual relationships established and maintained via interaction with other individuals or groups therefore determining the likelihood of a successful investment [40]. Zheng et al. [38] in 2014 coined the term 'relational social capital' in the crowdfunding literature thereby prompting research into the various aspects of relational social capital (trust and identity).

Trust is defined as a psychological state consisting of the purpose of accepting susceptibility based upon optimistic expectations of the purposes or behavior of another individual or network. Based on individual trust beliefs, trust can be distinguished into integrity-based trust which is entrenched in perceptions about the trustee's honesty, character and

motives and competence-based trust which refers to the trustor's awareness that the trustee possesses the interpersonal and technical competencies to fulfill their mandate [41].

MacMillan et al. [42] in the year 2005, found trust to be a significant factor in influencing the backers' intention to donate towards the project in form of actual finances (money) or marketing to their individual and or collective network via social media. Later on, in 2011, Bottazzi et al. [43] discovered that a venture capitalist's decision making is also positively or negatively impacted by trust or lack of thereof. However, this research on trust and crowdfunding performance did not adhere to a consistent classification of trust.

Due to this research gap, Chen et al. [44] in 2014 classified trust into two categories: trust in other CrowdBacker's or backers as well as trust placed in the transitional platforms. Later on, in 2016, Kang et al. [45] further classified trust into that which was resultant from outcome valuation (calculus trust) and that derived from relationships (relationship trust).

In crowdfunding, identity influences people's behavior patterns and the purpose of making investments; thus, backers are more likely to fund projects which are consistent with their own identity. Colombo et al. [46] earlier in 2015, proposed that the factors of crowdfunding share a sense of mutual identity. In the case of the Kickstarter platform, some 'advocates' established a rule called 'Kicking It Forward' (KIF), which requires proponents who have received funds from Kickstarter to methodically re-inject 5% of their profits in support of other projects.

Scholars who applied social identity theory in reward-based crowdfunding research explained that it plays an important role in investors' decisions in the crowdfunding community with emphasis on the interaction between social identity and other types of social capital [47]. In the following year of 2016, Kromidha and Robson [36] measured it as the totality of shares of project information on personal Facebook pages by backers and found that the degree to which they identified themselves as members of a collective, is positively linked with a project's success.

In the same year, 2016, Chen Q et al. [39] applied similar concepts as substitutions for social identities, such as group cohesion, which referred to the inter dependencies between group members and suggested that group cohesion impacted the effectiveness of social connection in the group, thereby increasing the project's success rate.

Separate and individual studies based on social exchange theory, claimed that establishing a backer's commitment offshoots their intention

to fund a crowdfunding project [48]. According to a paper written by Giudici et al. [49] in 2018, found that restricted compliance with social norms enhances the positive effect of local altruism on crowdfunding performance. Concurrently, Gleasure and Morgan [26] in the same year of 2018, established that social norms influenced crowdfunding by creating, filtering or regulating the nature of subject and rules and groups of collectives.

2.3.3. Cognitive social capital

According to Nahapiet and Ghoshal [50] cognitive social capital is defined as the resources which offer shared interpretations, representation and meaning in the collective network. In comparison to relational and structural social capital, cognitive social capital is almost scarcely researched on. In a paper written by Zheng et al. [38] in 2014 and in 2017 by Mamonov [51] are the only empirical studies known to us, which involved the relationship between cognitive social capital and crowdfunding performance. The former measured cognitive social capital as project description length and the latter, text mined the real estate project descriptions. However, Skirnevskiy et al. [52] argued that these forms of measurement cannot represent cognitive social capital therefore provided a significant research gap for future researchers.

The entrepreneurs' and backers' shared values can be derived from similar experiences (project outcome) and culture (social or corporate traditions) in a common geographical location or project categories. This therefore means that crowdfunding is not singularly fueled by economic benefits but also by a set of shared values which bond a group of investors and anchor them to certain projects. Some scholars share the opinion that shared values in the crowdfunding community will not only directly influence the investors' identity in the virtual community, but also make it simpler for repeat backers to fund their projects 25, 53.

Meanwhile, these shared values encourage backers to align their funding intentions towards more collective antecedents for the whole community, from individual self-interest. Empirical results verify that the degree to which a campaign goal is consistent with community culture positively affects project performance. In this regard, we find two empirical papers on shared values and crowdfunding [54, 55].

As per Zhao et al. [48] if both the entrepreneur and the Backers shared comparable values, there is a high level of commitment and trust between backers and entrepreneurs in reward-based crowdfunding. In the same year, Josefy et al. [56] established that these shared values

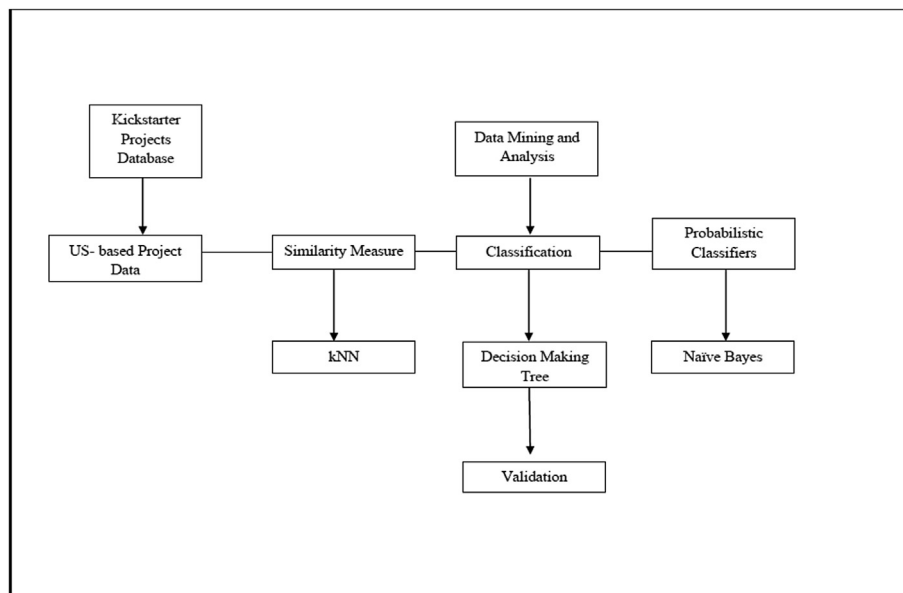


Figure 4. Conceptual Framework.

within a group of collectives are linked to trust, aligned behaviors, cooperation, judgement, individual and collective beliefs, amongst other things.

In summary, we have expounded on the applications of social capital as a link and bond that connects the entrepreneur to the backers thus influencing the project performance and outcome from the individual and collective perspective. In this paper, we seek to achieve the research objectives stated in the introduction, by use of Knowledge of Nearest Neighbor (kNN), Naïve Bayes and Decision Making Tree algorithms that will predict US based Kick-starter projects outcome and aid both the Entrepreneurs and Backers achieve information symmetry, reduce financial risk as well as improve resource distribution in the following conceptual framework.

3. Conceptual framework

This chapter of our paper seeks to clarify how the dimensions of social capital applied on crowdfunding can be measured, therefore answering the research questions that we put forward in the introduction. Figure 4 designed by us, demonstrates the various data mining techniques used in our research. We derived our dataset from <https://webrobots.io/kickstarter-datasets/> in Microsoft Excel, comma separated values (CSV) format and applied filtering methods and data mining techniques using Rapid Minor Software, to extract and analyze the main research variables as follows.

Independent variables:

- (a) The Number of Backers involved in the project (relational social capital); which is the collective sum of people who finance or contribute to the morale of a project, contingent on the individual and collective social capital that an entrepreneur and his/her team have in their personal, or corporate social networks. It also represents the initial backers who kick start the funding of the project and how through their help, get more backers to invest in a project.
- (b) The Time Duration of the project (dimension of context): which refers to the funding lifespan of the project from the time the project is created and then launched, to when the project's outcome is determined. This determines the success rate of the project.

Dependent variable:

- (c) The Converted Pledged Amount of Money (individual and collective performance): which refers to the total amount of money raised for the project against the project's goal, within a set time duration. The higher the number of backers involved in a project, the higher the amount of money raised, ceteris paribus.

Controlled variables:

- (d) The Project Category (structural social capital): which refers to the specific type of project that a crowdfunding platform is allowed to host. This also refers to the common social interest that brings together the entrepreneur and the project backers. Without a social personal or business interest it would be much harder for an entrepreneur to convince potential backers to invest their time, influence and money on a project. For the purpose of our research, we shall explore Arts, Music and Theatre which include 45 sub-categories
- (e) The Geographical Location of the project (dimension of context): which refers to the shared similarities in legal, socio-cultural, economic, technological environment, as well as distance location between the project backers and the entrepreneur(s). In this research, the geographical location of the projects will be the 41 states in The United States.

- (f) The Project Outcome/State (individual and collective performance outcome): Depending on the funding goal of a project and the purpose of this paper, the project outcome is classified into four categories: Live; meaning that a project is still being crowdfunded and its "fate" unknown. Successful; meaning a project's funding goal has been met and surpassed within the set time duration. Failed; meaning the project has not met its funding goals within the given time duration. This is mostly due to insufficient amounts of money raised. Cancelled; meaning a project has been discontinued.

In the initial dataset there were 3728 Kickstarter projects across 15 categories in 22 countries worldwide with US based projects amounting to 2579 projects i.e. 69 % of total projects which were collected in the duration of several years.

3.1. Data mining

Data mining involves the filtration and extraction of relevant information from massive volumes of data. This involves the study of pattern recognition which requires the application of different mining techniques and the training of algorithms to decipher and recognize patterns on sample sizes and then once the algorithm has yielded successful results, the algorithm will be applied on larger population sizes. Algorithms are designed for particular situations such as detecting data patterns through identification of similarities, probability testing, and decision making in order to solve specific problems.

It is fundamental to first and foremost understand that the following summarized data as shown in Table 1 which describes the number of Kickstarter projects in the US and their project outcome.

From the Table 1 across all categories, there are 1570 successful projects, 855 failed, 84 cancelled and 57 projects live or ongoing across 41 states in the US. From an inferential statistics perspective, the rule of thumb for deciding on a sample size should at least account for 30% of the population size when conducting an empirical study in order to avoid data anomalies thus, why we chose, Film, Music and Art categories which amounted to 1180 projects combined i.e. 46% of the population size.

After filtering for redundancies and anomalies in the 1180 projects we remained with 1157 projects. This paper implemented convenience sampling in determining to work with US based projects from the other 21 countries since the combined number of projects across The US accounted for almost 70% of all available projects in the Kickstarter database projects population. In order to avoid sampling bias and also

Table 1. The number of Kickstarter projects in the US and their project outcome.

Categories	Cancelled	Failed	Live	Successful	Total
Art	15	131	1	214	361
Comics	1	4	9	100	114
Crafts	5	57	1	58	121
Dance	0	5	0	57	62
Design	2	11	10	58	81
Fashion	2	31	2	52	87
Film	6	148	10	257	421
Food	10	67	4	68	149
Games	1	43	5	77	126
Journalism	7	58	2	45	112
Music	14	105	6	273	398
Photography	7	34	2	25	68
Publishing	4	42	3	172	221
Technology	7	105	14	89	215
Theatre	3	14	1	25	43
Total	84	855	57	1570	2579
Average	6	57	4	105	172

supported by some scholars works, we used cluster sampling to determine the afore mentioned 3 categories.

Upon conducting initial testing, we realized from the information in our database, that even though The US has 52 states, that there are only 41 states which actively participated in Kickstarter crowdfunding. Therefore, the data on the geographical location of the projects per US State and City or Town was also insufficient to run tests on and required mining even larger volumes of data in several databases which is time consuming. We therefore decided to conduct the tests on the acquired data that we had on the previously mentioned 3 project categories and variables which covered the 41 states.

In this paper, we applied 3 data mining techniques; similarity measures (kNN Algorithm), Probabilistic Classifiers (Naïve Bayes Algorithm) and Classification (Decision Tree Model and Algorithm) techniques. In order to compare the results of the classifier under test with trusted external judgments, we use precision and recall.

3.1.1. kNN algorithm

k-nearest neighbors may be a simple algorithm that stores all available cases and classifies new cases supported a similarity measure (e.g., distance functions). It's been utilized in statistical estimation and pattern recognition since the start of the 1970's as a non-parametric technique.

For the purpose of this research, we applied the kNN algorithm to classify the project category as well as the final project outcome of similar live projects based on, number of weeks it takes to raise a particular amount of money as well as the number of backers against the converted pledged amount of money raised towards the project.

The project outcomes were applied as control variables and were classified in to 4 classes whereby, 0 = Live, 1 = Successful, 2 = Failed and 3 = Cancelled projects. The Euclidean Distance was used to measure the project outcomes with similar patterns as shown in the following Eq. (1) with the value of k = 10 nearest neighbors. i.e. project outcomes and or categories with the similar variables as the unknown project.

$$\text{Distance of k, Project Outcome or Category} = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \quad (1)$$

Where:

- k = the project outcome and or category
- x_1 = the number of backers in the live project of unknown outcome.
- y_1 = the number of backers in the project of known outcome.
- x_2 = the converted pledged amount of money in the live project of unknown outcome.
- y_2 = the converted pledged amount of money in the project of known outcome.

3.1.2. Naïve Bayes

Naïve Bayes Classifiers are a family of straightforward "probabilistic classifiers" supported applying Bayes' theorem with strong (naïve) independence assumptions between the features. All Naive Bayes classifiers assume that the worth of a specific feature is independent of the worth of the other feature, given the category variable.

In this paper we used the Naïve Bayes to determine probability of projects having a successful, failed, cancelled or live outcome based on the converted pledged amount of money dependent on the number of backers across the accumulated afore mentioned three project categories as shown in the Eq. (2) using Bayesian probability terminology as below.

$$\text{Posterior} = \frac{\text{Prior} \times \text{Likelihood}}{\text{Evidence}} \quad (2)$$

The formula above can also be also stated as follows:

$$P(C_k|x) = \frac{p(C_k)p(x|C_k)}{p(x)} \quad (3)$$

Where:

- x = the number of backers in the crowdfunding project
- p = the instance probabilities of each project goal shown as $p(C_k | X_1, \dots, X_n)$.
- k = the number of possible project outcomes based on the amount of money raised
- C = the number of projects with the same outcome

3.1.3. Decision tree algorithm

Decision Tree algorithm belongs to the family of supervised learning algorithms. Unlike other supervised learning algorithms, the decision tree algorithm can be used for solving regression and classification problems too.

In this paper, we apply the deterministic decision tree model and algorithm to help the entrepreneur determine whether a longer time duration of the project results in an increase in the number of backers and the converted pledged amount of money thus positively affecting the project outcome.

In the instance where the output of a decision tree is $f(x)$, for all $x \in \{0,1\}^n$ whereby 0 and 1 represents the tree node (the point at which a decision is made), therefore the decision tree will determine f which is the project outcome. The intricacy of f is the minutest depth among all deterministic decision trees that compute the project outcome.

The root of our decision tree is hinged upon the least number of days it takes to achieve project success attributed with the least amount number of backers and least total converted pledged amount of money raised across all three project categories across the US.

In order to compare the results of the similarity measures, probabilistic classifiers and classification under test with trusted external judgments, we use precision and recall.

3.1.4. Precision and recall

As shown in Eqs. (4) and (5), Precision refers to the number of correct results divided by the number of all returned results and Recall, the percent of all relevant documents that is returned by the search. In precision and recall, we classify the project outcome based on 4 tasks:

- i. **True Positive (TP)**: which means that the projects with shorter time duration have more backers and therefore increased likelihood of success.
- ii. **False Positive (FP)**: which means that the projects with shorter time duration do not have more backers and therefore lesser likelihood of success i.e. a Type I error.
- iii. **True Negative (TN)**: which means that the projects with longer time duration have more backers and therefore increased likelihood of success.
- iv. **False Negative (FN)**: which means that projects with longer time duration do not necessarily have more backers and therefore, lesser likelihood of success i.e. a Type II error.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

In order to further evaluate the fraction of predictions that our models got right, for the projects of successful and failed outcome, we shall further apply accuracy and f-measure, which is referred to as the harmonic mean between precision and recall as shown in the Eqs. (6) and (7) respectively.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

Table 2. Correlation table between the project duration (in days), the number of backers and the amount of money raised towards a project.

	Backer's Count 1	Converted Amount Pledged	Days
Backer's Count	1		
Converted Pledged Amount	0.924859361	1	
Days	0.008826467	0.037680901	1

$$Accuracy = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{7}$$

4. Data analysis

Our first research objective is to determine whether the entrepreneur's structural social capital value is high enough to attract more potential backers who will financially and motivationally invest in the crowdfunding project therefore leading to a successful project outcome.

The following Table 2 is a correlation table between the project duration (in days), the number of backers and the amount of money raised towards a project.

From the correlation table above, we denote that the Number of backers involved in the Kickstarter projects positively and significantly influences the converted pledged amount of money raised towards the project with a 0.924 significance. However, the project duration has no impact on the backer's count with a 0.008 significance. At the same time, there is a 0.037 level of significance between the converted pledged amount and the project duration. This means that the impact of the duration of a project is insignificant on the converted pledged amount of money raised.

We therefore went further and attempted to establish the intertwined relationship between the geographical location of a project and the number of backers in the project as shown in Table 3.

From the Table 3 above, we determined that the State of Wisconsin has the highest number of backers, 10,035, that corresponds with the highest converted pledged amount of money, \$ 479,128 and the total time duration is quite short compared to other projects. We also noted that the State of Kansas had the projects with the lowest number of backers also a significantly longer time duration.

Using the 30:70 percent rule of testing we applied kNN to determine the outcome and sub category of the film projects using the Euclidean Distance for projects with unknown sub categories and outcomes based on the project duration and the converted pledged amount towards the project; as clearly illustrated in the Table 3 below.

In the Table 4, k = 10, meaning we were looking for 10 projects that had similar values. We were able to determine that two live projects were digital and most likely to have failed and successful outcomes in that order. The numerical values in the subcategory represented the value of the project outcomes as earlier stipulated in page 18. The Figure 5 below shows a clearer representation of the Table 4.

From the scatter plot above, we derived that the digital projects which had failed outcomes had similar characteristics with the cancelled ones i.e. the number of backers involved in the projects were between 0 and 1209 and had longer project duration whereas for the projects which were successful, the number of backers was higher at 1820 and above. This shows that successful projects with higher backer counts also had shorter time duration compared to the alternative projects.

We therefore ran the kNN algorithm on the rest of our sample size to further prove this and derived these results as summarized on the following Table 5 which is the confusion matrix. The results were an accuracy of 82.79% which means that there were 681 projects which were accurately identified as successful with a precision of 84.60%, 274 projects which were correctly identified as failed with a precision of 79.65% and only 2 projects which were correctly predicted as cancelled with a precision of 28.57% which means they could be identified as either cancelled or failed based on the scatter plot above. The f measure for the projects with only successful and failed outcomes was 90.55%, with a precision and recall of 86.97% and 94.45% respectively.

Using the same parameters, we conducted a comparison of the above kNN algorithm analysis with the Naïve Bayes (Bayesian method) algorithm which derived the following results as illustrated in the Table 6 that is also a confusion matrix.

The results from the above table differed quite significantly with the kNN findings with an accuracy of only 61.50% which means that there were 393 projects were likely to be accurately identified as successful with a precision of 93.79%, 290 projects which were correctly identified as failed with a precision of 48.96.%, 2 projects which were correctly predicted as live with a precision of 10.53% and the probability of identifying cancelled projects as such was 10.75%, with only 10 projects being correctly identified. The f measure for the projects with only successful and failed outcomes 72.17%, with a precision and recall of 96.79% and 57.54% respectively (see Figure 6).

Table 3. The intertwined relationship between the geographical location of a project and the number of backers in the project.

Geographical Location	Sum of backers count	Sum of converted pledged amount (\$)	Sum of Weeks
AK	420	26764	11
AL	57	3027	12
AR	91	1757	7
AZ	179	9276	40
CA	4130	329036	286
CO	540	37117	66
CU	30	7505	4
DC	21	1311	12
FL	820	58158	71
GA	476	24450	51
HI	11	831	4
IA	138	4831	7
ID	31	756	8
IL	318	24412	60
IN	7	68	12
KS	1	1	9
LA	63	3134	16
MA	1234	63937	63
MD	37	920	13
MI	379	62482	46
MN	470	33174	41
MO	65	6032	10
NC	65	7532	31
NH	59	3113	12
NJ	91	11993	16
NM	202	20061	32
NV	519	47894	41
NY	1624	199817	161
OH	984	28230	39
OK	30	3288	16
OR	740	47703	64
PA	896	84185	62
RI	186	18009	11
SC	96	7875	13
TN	166	22401	20
TW	62	6493	6
TX	612	53981	85
UT	38	2939	13
VA	389	34961	52
VT	189	9387	9
WA	622	36706	65
WI	10035	479128	21
Average	645.7857143	43447.02381	38.52380952
Grand Total	27168	1827965	1624

Table 4. The Euclidean Distance for projects with unknown sub categories and outcomes based on the project duration and the converted pledged amount towards the project.

Backer's Count	Converted Pledged amount	Weeks (W)	Sub Category	Euclidean Distance (WandAmt)	Rank Project	Outcome
	21	9	Digital 0	0	1	Failed
16	335	3	Digital 1	314	5	Successful
79	3943	5	Digital 1	3923	7	Successful
62	4492	4	Digital 1	4471	7	Successful
41	1820	4	Digital 1	1799	6	Successful
1	1	4	Digital 2	20	1	Failed
1	50	9	Digital 2	29	2	Failed
19	311	4	Digital 2	290	2	Failed
0	0	3	Digital 3	21	1	Cancelled
18	1209	6	Digital 3	1188	1	Cancelled

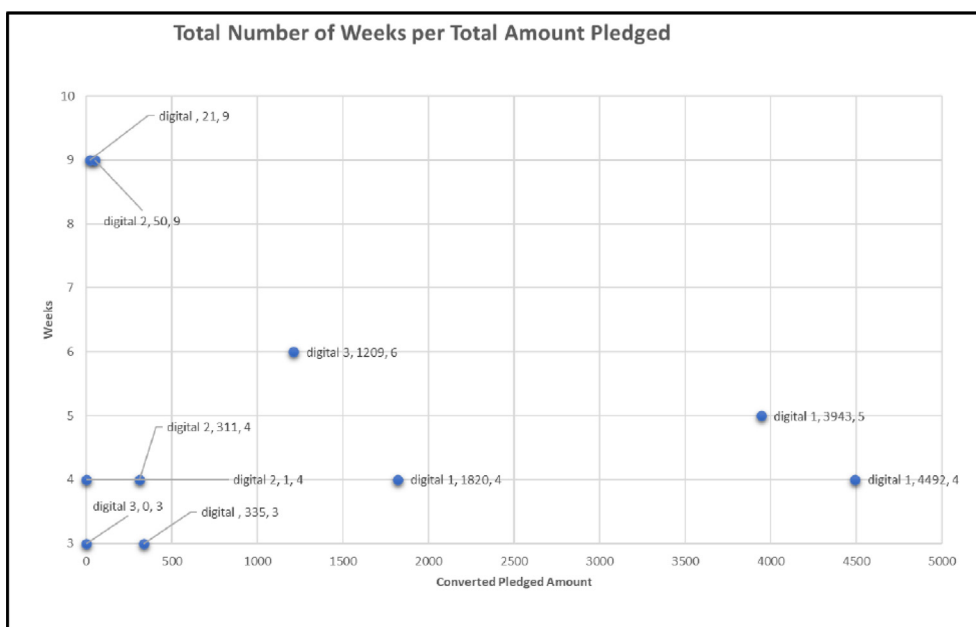


Figure 5. kNN prediction of the project outcome and category based on the converted pledged amount and the project duration in weeks.

Table 5. kNN and f measure for the projects with only successful and failed outcomes.

Accuracy: 82.79% ±2.06% (micro average: 82.79%)

True 1	True 2	True 0	True 3	Class precision	
Pred. 1	681	102	13	9	84.60%
Pred. 2	40	274	8	22	79.65%
Pred. 0	0	0	0	0	0.00%
Pred. 3	1	1	3	2	28.57%
Class Recall	94.32%	72.69%	0.00%	6.06%	

Table 6. The Naïve Bayes (Bayesian method) and f measure for the projects with only successful and failed outcomes.

Accuracy: 82.79% ± 2.06% (micro average: 82.79%)

True 1	True 2	True 0	True 3	Class precision	
Pred. 1	393	13	11	2	93.79%
Pred. 2	290	306	8	21	48.96%
Pred. 0	17	0	2	0	10.53%
Pred. 3	22	58	3	10	10.75%
Class Recall	54.43%	81.17%	8.33%	30.30%	

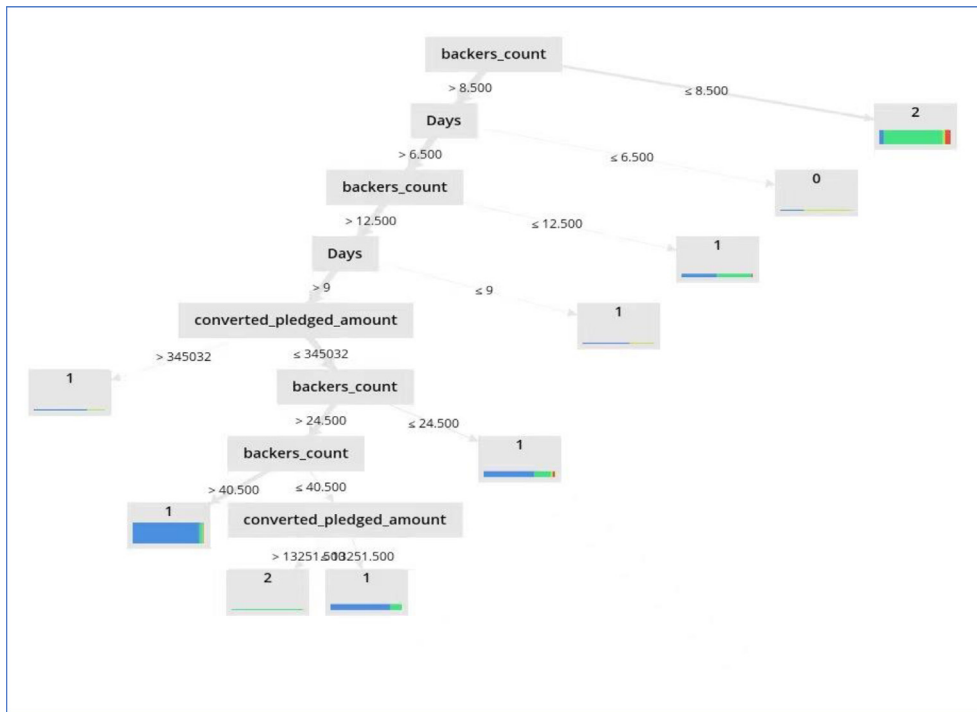


Figure 6. Decision Tree Diagram predicting project outcome against the project duration, the number of backers and the converted amount of money pledged.

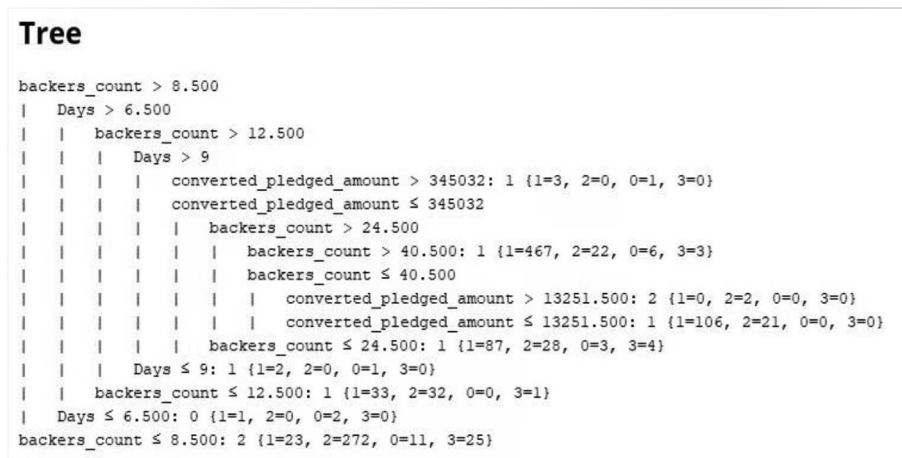


Figure 7. Decision Tree Diagram Algorithm predicting project outcome against the project duration, the number of backers and the converted amount of money pledged.

In comparison to the kNN algorithm we realized that using the Bayesian algorithm there was an increased likelihood of successful projects being predicted as failed therefore fulfilling the Type I error. Whereas in the kNN algorithm the likelihood of getting a type II error was higher. In order to reduce the risk of information asymmetry between the entrepreneur and the backers as well as the impact of negative social capital on crowdfunding outcome, we applied the use of the Decision Tree algorithm which is as illustrated in the following Figure 7.

Based on our dataset the following parameters were set: In order to achieve crowdfunding success across all three project categories, the backers count has to be more than 6,500 people but lower than 12,500 people. With a total converted pledged amount of 345,032 the probability of project success would be increased if the time duration of the project was more than 9 days. Whereby, the likelihood of a success project would be 3 successful projects, 0 failed, 1 live project

and 0 cancelled. As the backers count was above 24,500, there would be 2 probabilities; a backer's count that is lower than 40,500; whereby the possibility of project success decreases to 0 and the number of failed projects increases to 2 with 0 live projects and 0 cancelled projects. If the backer's count was higher than 40,500, then the likelihood of project success would increase to 467 successful projects, 22 failed, 6 live projects and 3, cancelled. The time duration of the projects of lesser than 8.5 and more than 6.5 days means that there would be 23 projects that would be successful, 272 failed, 11 live projects and 25 cancelled as shown in the algorithm 1.0 below.

We also applied the precision and recall method on our decision tree algorithm which resulted in an overall accuracy of 83.13% +/- 1.56%. which means that there were 687 projects were likely to be accurately identified as successful and 104 failed with a precision of 86.85% and recall of 95.28%. The f measure for the projects with only successful and

failed outcomes was 90.86%, with a precision and recall of 86.85% and 95.28% respectively. Whereby the actual precision was 791 projects and actual recall, 721 projects.

5. Conclusions

This research paper initially sought to determine the impact of structural and relational capital in Kickstarter projects across the US. From the Decision Tree Diagram, we have determined that even though, an increase in the backer's count might lead to an increase in the converted pledged amount and possibly influence project outcome, the likelihood of project success decreases.

The entrepreneur needs to note that the initial 9 days of the project are crucial because if the number of backers does not increase, then the likelihood of project failing or being cancelled increases. Therefore, there is the fundamental need for the entrepreneur to figure out a suitable and effective strategy that will result in strengthening the relational and structural social capital at an individual and collective level.

There was also very little evidence of whether the geographical location of the project would influence the number of backers in the project based on shared culture and social networks. This therefore provides an opportunity for future research.

This is an innovative paper as it applies these three data mining techniques in this way on Kickstarter projects datasets. However, kNN, Naïve Bayes and Decision Tree Diagrams have been applied in varied areas including the application of kNN in MapReduce technique in Data Mining [57], the application of Naïve Bayes as one among several used predictors of success for crowdfunding campaigns via textual classification of Kickstarter data based on project description which yielded lower accuracy and f measure of 58.2% and 56.75% respectively compared to our findings [58].

Declarations

Author contribution statement

Joseph O. Onginjo: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Dong Mei Zhou: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Tesema Fiseha Berhanu: Conceived and designed the experiments; Performed the experiments.

Sime Welde Gebrile Belihu: Contributed reagents, materials, analysis tools or data.

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Data will be made available on request.

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The authors declare no conflict of interest.

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